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An integrated systematic analysis of uncertainties in UK energy transition pathways

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HIGHLIGHTS

- Strategies to transition energy systems must contend with multiple uncertainties.
- Paper details approach to uncertainty analysis, linked to global sensitivity analysis.
- Key uncertainties strongly impact the costs and feasibility of required mitigation.
- An iterative approach between analyst and policy maker is required.

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ABSTRACT

Policy goals to transition national energy systems to meet decarbonisation and security goals must contend with multiple overlapping uncertainties. These uncertainties are pervasive through the complex nature of the system, the long term consequences of decisions, and in the models and analytical approaches used. These greatly increase the challenges of informing robust decision making. Energy system studies have tended not to address uncertainty in a systematic manner, relying on simple scenario or sensitivity analysis. This paper utilises an innovative UK energy system model, ESME, which characterises multiple uncertainties via probability distributions and propagates these uncertainties to explore trade-offs in cost effective energy transition scenarios. A linked global sensitivity analysis is used to explore the uncertainties that have most impact on the transition. The analysis highlights the strong impact of uncertainty on delivering the required emission reductions, and the need for an appropriate carbon price. Biomass availability, gas prices and nuclear capital costs emerge as critical uncertainties in delivering emission reductions. Further developing this approach for policy requires an iterative process to ensure a complete understanding and representation of different uncertainties in meeting mitigation policy objectives.

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1. Introduction

1.1. Importance of systemic analysis of uncertainty in energy policy

Energy policy makers at the national government level are wrestling with a “trilemma” of challenges relating to energy decarbonisation, security of supply and rising energy prices (DECC, 2011). These policy challenges have multiple overlapping uncertainties, which are pervasive through the complex nature of the system, and the long term consequences of decisions (Lempert et al., 2003). This growing focus on uncertainty analysis in complex systems is mirrored at the international level for the needs of key energy and environmental decision makers (e.g., IPCC, 2014).

The challenge of understanding, assessing and communicating uncertainties is magnified by the explosion in the range and sophistication in the models and analytical approaches used (Davies et al., 2014). In response to policy makers' difficulties in assessing uncertainties, modellers have repeated calls to improve the frequency, sophistication and transparency of uncertainty analysis in computational modelling of energy, environmental and economic interactions (Morgan and Small, 1992; Kann and Weyant, 2000; Risbey et al., 2005; Pfenninger et al., 2014; Usher and Strachan, 2012).

There is a long track record of energy models underpinning major energy policy initiatives, producing a large and vibrant research community and a broad range of energy modelling approaches (Jebaraj and Iniyar, 2006). Modelling collaborations have been an important tool to benchmark models, addressing specific analytical questions (van Vuuren et al., 2006) and advancing the

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state-of-the-art in modelling (Hourcade et al., 2006). Throughout this long track record there has been a tension between policy makers who need to make robust decisions under pervasive uncertainties, and modellers whose analytical outputs are designed to produce insights (Huntington et al., 1982).

The most common approach for dealing with uncertainty in large-scale energy modelling is local sensitivity analysis on key inputs to which a model is expected to be most sensitive (Saltelli and Annoni, 2010). However, such approaches are limited as they fail to capture the importance and impact of multiple uncertainties. This paper describes a novel approach using an innovative UK energy system model, ESME (Pye et al., 2014b), which characterises multiple uncertainties via probability distributions and propagates these uncertainties to explore trade-offs in cost effective energy transition scenarios. A global sensitivity analysis is then undertaken to explore the uncertainties that have most impact in the long term mitigation pathways.

1.2. Application to UK decarbonisation pathways

The international scientific and governance communities have reached a consensus that climate change presents a severe barrier to future human well-being and livelihoods (IPCC, 2014). In response, the UK was the first G20 country to legislate GHG reduction targets, of at least –34% by 2020 and exponentially declining to –80% by 2050, relative to a 1990 baseline (HMG, 2008). A range of policy mechanisms (DECC, 2011) are now in place to put the UK on a path to meeting this long-term stringent target, with the setting of five-year carbon budgets by the independent governmental advisory body (CCC, 2008).

Although the UK is one of the few countries on track to meet its GHG targets, the remit of UK energy and environmental policy has been substantially aided by long term structural reform e.g., the dismantling of the nationalised and unionised power sector, the continued restructuring of the economy from industry to services and the impact of the financial crisis and subsequent recession. As the UK (similarly to other OECD economies) recovers from recession and hence pressures on emissions continue to grow, the debate over strategies and costs of long term decarbonisation under a range of national and global uncertainties is becoming ever more heated (Ekins et al., 2011).

In its recent review of the 4th Carbon Budget (CCC, 2013), the Committee on Climate Change (CCC) reiterated the need for early action to reduce emissions out to 2030, to ensure the UK was on a pathway to meeting the longer term 2050 target. It concluded that the budget should be kept at the level provided in its original advice to Government (CCC, 2010), rather than tightened, but that the aim should still be to achieve early decarbonisation of the power sector, in addition to strong action across other sectors. The CCC deem this critical if the UK is to follow a cost-effective path towards decarbonisation, and avoid the additional costs associated with delayed action.

However, key uncertainties exist around the delivery and cost of the 4th Carbon Budget and 2050 target, such as economic growth and structural change, delivery capacity (including financing), technology costs and behavioural change. The uncertainties are of fundamental importance, given the large investments required to fund this transition, and because these investment decisions will result in long term consequences around the direction of the transition. The CCC (2013) estimate that total capital costs of scenarios to decarbonise the power sector to an intensity of 50 g CO₂/kWh by 2030 could be of the order of £200 billion cumulatively.

1.3. Research aims and layout of the paper

The objective of this paper is to explore the impact of technological and economic uncertainties critical to delivery of a lower carbon energy system. The task is performed using an energy systems model (ESME) which provides a framework for the systematic analysis of multiple uncertainties on target delivery and technology pathways out to 2050 (see Section 2). This assessment of the complex and interacting energy system is strengthened by a linked global sensitivity analysis which identifies key and non-influential uncertainties affecting the cost-effective pathway. Section 3 discusses selected results focusing on how uncertainties impact on achieving emission reduction targets, the importance of technologies and fuels in delivering targets, and the uncertainties that are revealed as most critical in the transition to a low-carbon energy system. In Section 4, we discuss the key insights, and in Section 5, how understanding the impact of uncertainty on the system is critical for policymaking, and on the opportunities for improved modelling in the structuring, assessment and communication of key uncertainties.

2. Methods

2.1. Uncertainty in energy systems models

Since 2003, many energy system modelling studies have been undertaken to support UK energy and climate strategy development. Most studies have been deterministic in approach, capturing the range of uncertainty using simple scenario sensitivity analysis on parameters (DTI, 2003; Strachan et al., 2009; AEA, 2011). While arguably playing a critical role in supporting the development of UK long term strategy, many of these studies have not addressed the uncertainties surrounding the transition to a low carbon system in an integrated and systematic manner. Usher and Strachan (2012) argue that applying a deterministic methodology to a complex and multi-faceted area of strategy development that is inherently uncertain is problematic. They highlight three key problems with simple sensitivity analysis – (i) the probability of an input value cannot be quantified, (ii) disparate sensitivity scenarios make policy insights more difficult to determine and (iii) the cost of uncertainty is unknown.

The strategies informed by such modelling have to consider uncertainties that fall into questions of ‘post-normal science’ (Funtowicz and Ravetz, 1990), where both decision stakes and uncertainty levels are high (Keirstead and Shah, 2013). The decisions made about energy systems have significant consequences (stakes are high) while the complexity of the system makes it difficult to determine the outcomes of different decisions (uncertainty is high). While the strategic decision has been taken to transition to a low carbon economy in the UK, there remain a multitude of decisions relating to investment that need to be considered, and the policies to incentivise these investments.

In this paper, a probabilistic approach is used, combined with an integrated systematic sensitivity analysis to explore the effects of parametric uncertainty on the model outputs. Keirstead and Shah (2013) argue that global sensitivity analysis techniques should be used in conjunction with uncertainty analysis, to help decision-makers gain a robust understanding of system behaviour. Saltelli et al. (2008) define sensitivity analysis as the study of how uncertainty on a model output can be apportioned to different sources of uncertainty in the model input, whereas uncertainty analysis is concerned with quantifying uncertainty in the model output. In effect, global sensitivity analysis seeks to answer questions around what are the most important uncertainties in the system.

2.2. Uncertainty analysis using ESME model

Energy Systems Modelling Environment (ESME), developed by the Energy Technologies Institute (ETI), is a fully integrated energy systems model (ESM), used to inform the ETI's technology strategy about the types and levels of investment to make in low carbon technologies, to help achieve the UK's long term carbon reduction targets (Heaton, 2014; Pye et al., 2014a). Built in the AIMMS environment, the model uses linear programming to assess cost-optimal technology portfolios. The mathematical programme is similar to that used in other bottom-up, optimisation models, such as MARKAL-TIMES (Loulou et al., 2005), where the objective function is to maximise total economic surplus, subject to pre-defined technology capacity and activity constraints, as well as policy constraints (e.g., Renewable Energy target). The total economic surplus is calculated as the sum of the discounted system wide costs, including the change in consumer surplus and costs associated with technology investment and operation, and resource commodities.

Max total surplus

$$\begin{aligned}
 &= \sum_t Y_t \times DF_t + \left(\sum_k IC_{k,t} + FC_{k,t} + VC_{k,t} + \sum_l IC_{l,t} + \sum_g IC_{g,t} \right. \\
 &\quad + FC_{g,t} + VC_{g,t} + \sum_{x \in R} IC_{x,t} + FC_{x,t} + VC_{x,t} + \sum_{x \in R} RC_{x,t} \\
 &\quad \left. + \sum_x ElastC_{x,t} \right) \quad \forall k, l, g, x, t \in \mathbb{N} \quad (1)
 \end{aligned}$$

where Y are the years defined per time period t , DF is the discount factor applied, IC , FC and VC are the investment, fixed and variable costs of the production k , retrofit l , storage g and transmission x technologies. RC refers to the set defining resources, the x group are the system energy commodities and $ElastC$ is the variable defining the consumer surplus (reflecting demand response).

A key feature of the model is that uncertainty around cost and performance of different technologies and resource prices is captured via a probabilistic methodology, using Monte Carlo sampling techniques. A four step approach is used in the analysis; firstly, a set of carbon prices are derived via a deterministic model run that approximates the reductions required under a given target cap. Secondly, a range of uncertainties are defined and introduced into the model. Thirdly, the model is run in probabilistic mode using the deterministically derived carbon prices to assess target delivery under uncertainty. Finally, sensitivity analysis is used to explore the impact of different uncertainties.

2.3. Approach to sensitivity analysis

Following the guidance and setting types described by Saltelli et al. (2008), the goal of our sensitivity analysis is first defined, to identify key uncertainties that impact on the likelihood of meeting UK emission reduction targets. The following sensitivity analysis settings are relevant – (1) *Factor prioritisation*, used to identify the variables that after being fixed to their 'true' values would lead to the greatest reduction in variance of the output, and (2) *Factor fixing*, used to identify the factors of the model that, if left free to vary within their specified ranges, would have no significant contribution in the variance of the output.

The sensitivity analysis performed in this work is comprised of two main steps; firstly, the correlation of each uncertain input with the output variables of interest, namely total system cost and total emissions, are investigated using scatterplots. Although scatterplots provide a useful starting point, marginal differences between factors can be difficult to differentiate. Secondly, a multivariate linear regression of the output variables is performed and a sub-model of the original model for each output variable of interest is derived. By means of the standardised regression coefficients (SRCs), ranking of uncertain input factors in each model output is obtained, whose precision is subject to the accuracy of the linear fit of the sub-model to the original model and to the degree of correlation between the variables.

In a multivariate regression analysis, the regression coefficients are a measure of the linear sensitivity of the outputs y to the inputs z_j , with SRCs obtained by multiplying the original regression coefficients by the ratio of the estimated standard deviations of z_j and y , to provide a useful measure of uncertainty importance for the input factors (Morgan and Small, 1992). The main advantages of using SRC as an uncertainty metric are both the lack of complexity of their calculation and their independency of the units or scale of the inputs and outputs being analysed.

It is common practice in other scientific fields to produce meta-models of a more complex original model in order to reduce the computational and analytical burden of producing a useful interpretation of the results. In research focused on simulation modelling of the built environment, Hygh et al. (2012) present multivariate regression as an energy assessment tool for early building design. In their work the original model was a non-linear building design model, and SRCs were used as a sensitivity measure to determine the importance of the design parameters in building energy consumption.

Although useful, SRC only captures first order interactions within the model, not quadratic or higher order effects. In this sense, Saltelli and Annoni (2010) highlight the fact that although linear regression is in principle predicated on model linearity, it can be taken further by being a good estimator of the degree of

Table 1
Input assumptions characterised using probability distributions.

Input parameter	Description	Source of uncertainty data
Investment costs – power generation	Includes all power generation technologies	Initial uncertainties based on 2020 ranges in DECC (2013a). Uncertainties extrapolated to 2050 based on different growth rates, according to maturity of technology.
Build rates – power generation	For key technologies including CCS, nuclear and wind	Own assumptions. Annual build rates varied by 50%
Investment costs – hydrogen production	Included all hydrogen production technologies	ETI (as used in ESME v3.2)
Investment costs – cars	For both small (A/B) and large (C/D) cars	AEA (2012) and Element Energy (2013)
Investment costs – heat pumps (HP), district heating (DH)		HP from University of Cardiff Chaudry et al. 2014), DH from ETI (as used in ESME v3.2)
Resource availability – biomass	Max annual availability of biomass (incl. imports)	CCC (2011), Bioenergy review.
Resource prices	Including fossil fuels and biomass	DECC (2013b) for fossil fuels, E4tec (2012) and Redpoint (2012) for biomass.

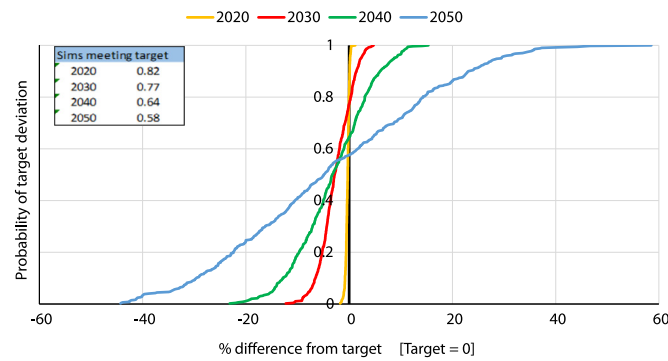


Fig. 1. Probability of % deviation from targets across model years under Reference carbon prices.

non-linearity of the model by means of the model coefficient of determination R^2 . It is important to make clear that each of the regression models are unique for a given Monte Carlo run, and therefore the results of this exercise are specific to a given model run. Following this logic, the regression sub-models obtained for the total cost and emissions outputs in the form of Eq. (3) are not intended to be used for forecasting or other prediction purposes other than ranking the importance of the uncertain input variables for that specific Monte Carlo run.

The regression model obtained for each of the output variables under analysis follows a generic linear form as expressed below:

$$y(i) = b_0 + \sum_{j=1}^r b_{z_j} z_j^{(i)} \quad \forall i = 1, \dots, N \quad (2)$$

where i represent the 500 Monte Carlo samples obtained for each of the z_j uncertain parameters, b_0 is the constant of the regression model and b_{z_j} are the regression coefficients. Each sub-model has a specific value of R^2 which informs of the linearity of the original model. Eq. (3) shows in a matrix form the structure of the data obtained in the analysis, where $Z_{r,N}$ are the points obtained by the Monte Carlo sampling, B_r are the original model coefficients and y_N are the output obtained with the ESME model.

$$\begin{bmatrix} z_1^{(1)} & \dots & z_r^{(1)} \\ \vdots & \ddots & \vdots \\ z_1^{(N)} & \dots & z_r^{(N)} \end{bmatrix} \begin{bmatrix} B_1 \\ \vdots \\ B_r \end{bmatrix} = \begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} \quad \forall j = 1, \dots, r \quad (3)$$

2.4. Model set-up and selection of uncertainties

2.4.1. Determining reference carbon prices

The first step in the analysis is to align the model to assumptions underpinning the 4th Carbon Budget review (CCC, 2013). This provides the basis for deriving reference carbon prices which, in the deterministically run model, deliver the carbon budgets and long term target. Alignment means that the emission target is consistent with national policy, includes known policies such as the renewable energy target, and uses a set of input assumptions consistent with government for those technologies and commodities which are of most interest in respect of system uncertainties. An overview of the assumptions is provided in Appendix A.

The derived carbon prices from this run are £13/tCO₂ in 2020, and £133, £226 and £421/tCO₂ for each 10 year time step out to 2050. They reflect the marginal costs of domestic mitigation, given the representation of the energy system, and the different technology and resource constraints. They are broadly within the range of estimates observed in other energy system modelling studies

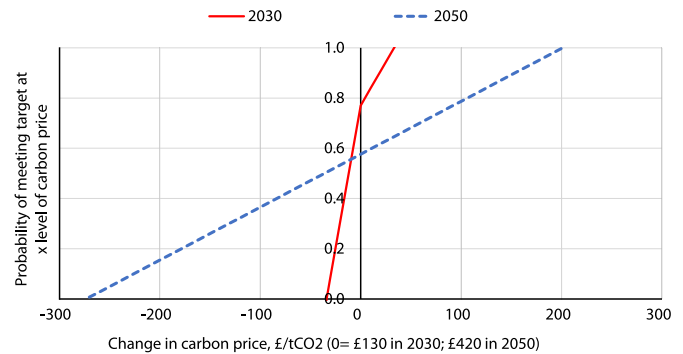


Fig. 2. Impact of change in carbon price on probability of meeting targets in 2030 and 2050.

(AEA, 2011).¹

The deterministic pathway can be characterised by changes to key sectors. The 2030 power generation profile has a carbon intensity of 89 gCO₂/kWh and delivers an 80% reduction on 2010 levels, compared to 88% in the CCC (2013) analysis. Out to 2050, the role of gas continues due to increased build of CCGT w/CCS (40 GW installed by 2050), while nuclear capacity grows significantly, to 32 GW by 2050. The use of IGCC biomass generation with CCS means that carbon intensity of generation is negative by 2040. Transport sector emissions are 34% lower in 2030 relative to the 2010 level, compared to the CCC reduction level of 42% (relative to 2012). This is due to slower penetration of electric vehicles in the ESME run; take-up only occurs at very high volumes in the 2030s, while in the CCC analysis, 60% of new car purchases are electric vehicles by 2030. Buildings sector emissions fall by 37%, relative to 2010 levels, a larger reduction than in the CCC analysis, reflecting a more optimistic view concerning the penetration of district heating. A 39% reduction in industry sector emissions is in line with the CCC analysis.

2.4.2. Model uncertainties

The model input uncertainties were identified both through expert consultation with the UKERC uncertainties project team (Watson et al., 2014) and based on the CCC (2013) analysis, which identifies key uncertainties based on the emergence of critical technologies and fuels underpinning the pathway. Given the lack

¹ These carbon prices differ significantly from those used in the CCC analysis, and for government policy appraisal (DECC 2009). However, CCC's cost effective pathway is not determined solely by investments only incentivised by a carbon price, recognising earlier deployment of technologies that are not cost-effective is necessary to ensure timely development and to reduce long term risk concerning their deployment.

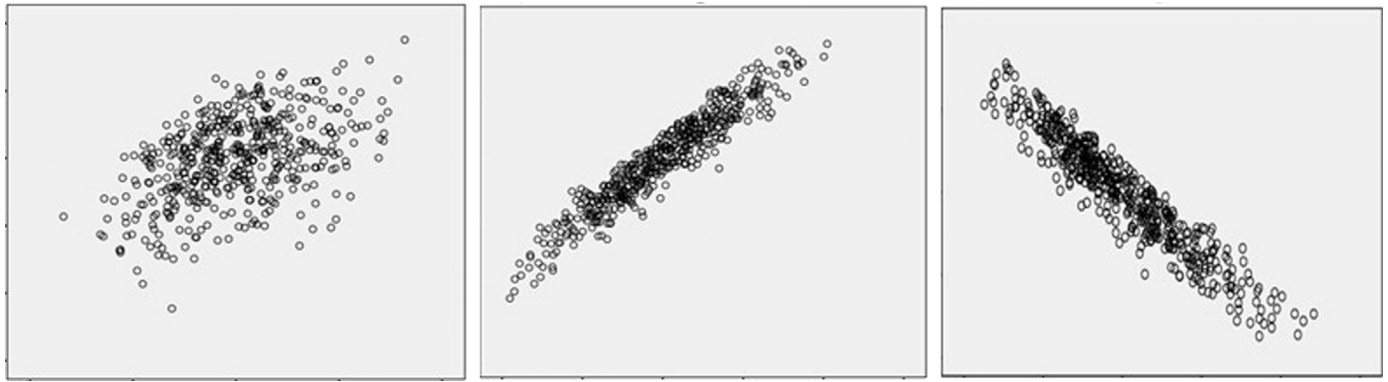


Fig. 3. Scatterplots of nuclear power plant costs, gas prices and biomass resource availability versus total system costs.

of available data on future uncertainties, a compromise was made to take a more simplistic but systematic approach, consulting with expert colleagues, focusing on key delivery technologies and reviewing range estimates from the literature (Table 1). From this, probability distributions were constructed, relying on triangular distributions. As argued in Biegler et al. (2011), and Emhjellen et al. (2002), in view of a lack of data, triangular distributions are valid for representing preferences over a certain value with symmetric or asymmetric variations around it. Appendix A contains further details of the modelling set-up and key assumptions.

Monte Carlo simulations were used to propagate the probability distributions on input assumptions through the model. The number of model runs that adequately cover the uncertainty space were estimated based on Eq. (4), introduced by Morgan and Small (1992) for a 95% confidence interval. The precision of the interval selected was based on estimating the true mean of the sample with less than 1% error. The number of model runs required to obtain less than 1% error in the mean estimation was 475.

$$n > \left(\frac{2cs}{w\epsilon} \right)^2 \quad (4)$$

where c is the deviation enclosing 95% of the probability, s is the standard deviation of the sample ($\text{£}7.41 \times 10^9$) and w is the width of the interval desired ($\text{£}2.63 \times 10^9$).

The model is then run for 500 simulations,² propagating the sampled values through each simulation. As demand response is also being characterised in this analysis, each simulation requires a calibration run to estimate demand curves, increasing the model run number to 1000. The model is run in 10 year periods, for a time horizon of 2010–2050. A discount factor of 3.5% is used, as per UK Government policy appraisal guidance in The Green Book (HMT, 2003), to discount system wide costs back to 2010 (as per standard NPV calculation). Three sets of simulations have been run. The first uses the set of carbon prices from the deterministic reference pathway, to assess how uncertainty impacts on meeting mid to long term carbon targets. Two additional sets of simulations are run, under lower and higher carbon prices (+/–25%) to investigate how changes in carbon prices impact on the probability of target delivery.

3. Results

3.1. Meeting targets under uncertainty

By running the model under a set of carbon prices, in effect

Table 2

Statistical tests for the multivariate regression analysis.

Statistic	Description	Benchmark value
R-square	Goodness of the model fit-Linearity evaluation parameter	~0.9
B-Partial Correlation coefficient	Ranking of variables by their impact on the variance of the output	Rank
p-Value	Relevance of the parameter in the model	< 0.05
Variance inflation factor	Measure of collinearity	> 10
Pearson correlation	Correlations between variables	> 0.8

placing a carbon tax on each tonne of CO₂, we can assess whether or not future emission reduction targets are achieved. Carbon prices are being used as a proxy target, having been derived from running the model deterministically under an emission cap (Section 2.4.1), representing the 4th Carbon Budget and longer term 2050 target. Technology and resource uncertainties mean that these carbon prices may not deliver the necessary reduction, or may over-deliver.

Fig. 1 shows the probability of meeting the targets in a given year. The probability of missing increases later in the time period due to increasing uncertainty. In 2050, 42% of runs do not achieve the target while in 2030, the probability is 27%. In addition, the level of deviation in 2050 is much larger than in 2030, where it never exceeds 5%; of course, a 1% deviation in 2030 is equivalent to emissions that are three times higher than in 2050. The observed pattern is one that would be expected; lower uncertainties in the near term mean that the reference carbon price is going to ensure a higher percentage of simulations meet the target, and that the average deviation from the target value will be lower.

From this, we can surmise that a given carbon price may or may not be sufficient to incentivise action. How far this uncertainty is to be mitigated (and by when) is a question for policy makers. This will in part be dependent on the impact of an incremental rise in the carbon price on the probability of meeting a target or not. To explore this, a set of high and low carbon price simulations were run, based on a 25% increase/decrease on the reference carbon prices.³ The results show how an increase in carbon price can increase the probability of meeting the target, thereby mitigating uncertainty (Fig. 2). Carbon price sensitivity is high in 2030; a £35 reduction in price (or 26% reduction) reduces the probability of meeting the target to zero. Conversely, a £30 increase leads to a 100% probability of meeting the target. This sensitivity in the mid-

² For computational reasons, a sample size of 500 was used.

³ DECC (2009) actually assume a +/-50% range on their carbon price estimates, albeit on lower absolute values.

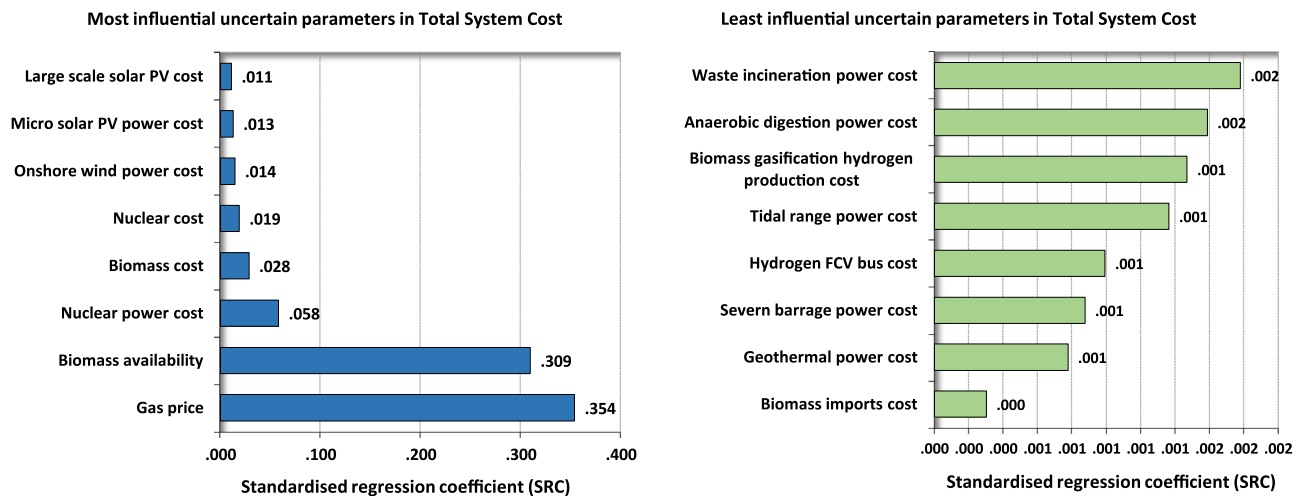


Fig. 4. Standard regression coefficients (SRCs) parameter rank from multivariate regression analysis – total system costs.

term means an insufficient price can adversely affect the probability of staying on the proposed transition pathway but that a modest increase can strongly mitigate the uncertainty of meeting the target level.

In 2050, carbon price sensitivity is much lower, as shown by the dashed series in Fig. 2. Therefore, managing the probability of meeting the target (or not) in 2050 requires much larger shifts in the carbon price. A limitation of this analysis is that it only uses two additional sets of simulations to construct this sensitivity metric; a more robust relationship between the carbon price and target delivery could be developed by running a larger number of alternative carbon price simulations.

3.2. Identifying key uncertainties through sensitivity analysis

Sensitivity analysis helps identify those input uncertainties that are influential in determining the probability of meeting the targets or not, and directs further investigation. Our chosen output metrics for this analysis are total system costs (as this is the model's objective function) and total emissions (as the policy relevant constraint).

The first step of the sensitivity analysis is to observe scatterplots, to assess how correlated input uncertainties are with the above output metrics. For total system costs, the obvious correlations include, from left to right in Fig. 3, nuclear capital costs, gas price and biomass resource availability (total cost is on vertical axis). This suggests that all three factors independently have an important impact on total system costs. For total CO₂ emissions, biomass resource availability provides the only obvious pattern (with lower emissions at higher availability).

A second step is to perform a multivariate linear regression, using standardised regression coefficients (SRCs) as first order sensitivity indices to rank the uncertain parameters by their impact on the outputs analysed. In order to test the validity of these indexes we check three statistical metrics of each of the regression models obtained by means of the multivariate linear regression equations (see Eq. (3)) obtained for the two output metrics of interest as presented in Table 2.

The models obtained for the total system costs and emissions show a correct goodness of fit with *R*-squared values of 0.99 and 0.874 respectively proving the goodness of fit of the corresponding linear regression models to the data and the linearity of the original model. Once the validity of the models is tested, the ranking of the uncertain parameters is performed based on the absolute values of their respective SRCs. The initial ranking is then filtered

by the *p*-values or significance levels obtained for each parameter. The parameters with *p*-values lower than 0.05 are considered as important or otherwise removed from the rank.

Then potential collinearity problems of the model are explored by using the variance inflation factor (VIF) metric. The parameters presenting VIF values higher than 10 are removed from the importance rank. VIF is an indicator of the correlation of one parameter with others in the model, and therefore separated from the analysis the importance effect from purely correlation effects. A similar analysis is performed for the least influential parameters in the model. The results of the sensitivity analysis and the respective rank of most (factor prioritisation) and least influential (factor fixing) parameters for the total system costs are presented in Fig. 4.

The most important parameters include those revealed in the scatterplots, particularly gas price and biomass availability. Nuclear power costs are important, although much less so than the aforementioned inputs. The continued importance of gas in CCS power generation means a strong impact on system costs when resource cost increases, and highlights potential security of supply risks. Reduced availability of biomass has significant implications for costs, given its critical use in CCS technologies in the longer term. Uncertainties of less relevance include biomass import costs and a range of renewable technologies, including geothermal, tidal barrage and range, and recovered bioenergy based power technologies. Imported biomass cost uncertainty is less important in later periods, as the model wants to utilise biomass as much as possible, and therefore availability is key as opposed to cost. The range of renewable technologies appear less important as they emerge in few of the model simulations.

Concerning emission levels in 2050, the most influential parameter is biomass availability (Fig. 5). Gas prices, nuclear power costs, and a range of renewable generation technologies follow in the ranking, albeit having much smaller values. Interestingly, some of the technologies do not appear in the cost metric ranking, highlighting the potential importance of selected technologies for emission reduction, despite limited impact on costs. Least influential parameters are broadly consistent with the cost metric analysis.

3.3. Sector based insights

The results in Section 3.1 provide the aggregate impact of uncertainty on results, while Section 3.2 begins to identify the key uncertainties. Guided by the sensitivity analysis, this section

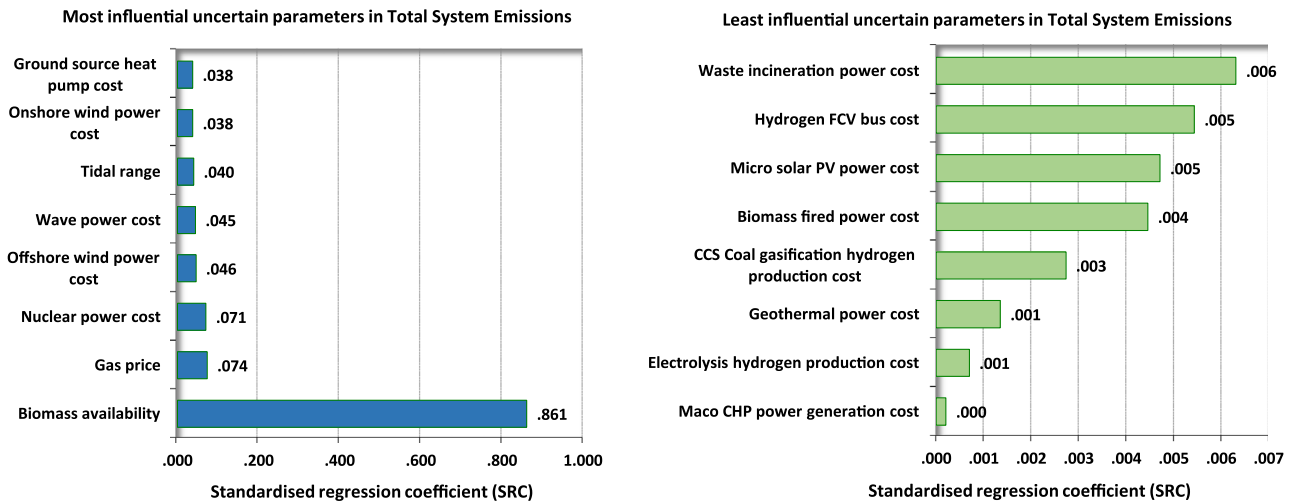


Fig. 5. Standard regression coefficients from multivariate regression analysis – total system emissions.

explores in more detail the role of different technologies by sector, and those prominent in the delivery of emission reduction targets.

3.3.1. Power generation system evolution

A first observation, despite uncertainties, is the criticality of power sector decarbonisation. Carbon intensity decreases substantially across all simulations, from a current level of just under 500 gCO₂/kWh, reflecting the cost-effective mitigation available in this sector (Fig. 6). However, it is also evident that carbon intensity levels are generally lower in simulations meeting the target (MT) versus those that do not (NMT), and supports the CCC guidance that a low carbon intensity of generation is required by 2030 to stay on a pathway to meeting the long term target (CCC, 2013). The important role of biomass-based CCS technologies in 2050 is also evident, with negative carbon intensities achieved through capturing and storing emissions from biomass deemed to be carbon neutral.⁴

System uncertainties do not appear to undermine the investment in low carbon generation (as observed above). All simulations also show high levels of electrification, with limited differences in generation levels. The distribution of generation by technology in 2030 is shown in Fig. 7. The main difference is between CCGT and nuclear; nuclear generation is on average higher in simulations that meet the target, while CCGT is lower. The probability of a generation level from CCGT w/CCS is broadly consistent between the two time series, and higher than other generation types, indicating the importance of this technology in 2030 irrespective of uncertainties.

In 2050, the generation by technology does not differ significantly between the two sets of simulations, with nuclear or CCGT w/CCS dominating. The carbon intensity differences observed in Fig. 6 are primarily due to the level of uptake of biomass IGCC w/CCS. With most technologies being near-zero or zero carbon, this technology drives differences in the carbon intensity levels, even at relatively low levels of generation. Uncertainty around gas prices and nuclear costs appear to be key determinants of technology investment decisions in the power sector, as shown by the sensitivity analysis.

⁴ This carbon intensity figure does not reflect negative emissions from hydrogen generation, where it uses hydrogen produced via biomass w/CCS technology.

3.3.2. Road transport car technology uptake

Car-based transport, accounting for 55% of transport emissions in 2010, requires strong mitigation action to meet targets. Differences between simulations that meet or do not meet targets are less evident in 2030, with the role of the sector in mitigation more pronounced in the longer term. Uptake of hybrid and electric vehicles is slightly higher in simulations that meet the target (Fig. 8). The continued role of ICE vehicles reflects more effort in other sectors, the use of biofuels and assumed efficiency gains by 2030.

By 2050, the role of electric vehicles is much more established, with over 25 million vehicles in 65% of the simulations (irrespective of meeting the target or not), reflecting the electrification of the system. Where the target is met, those simulations tend to show a stronger role for hydrogen and reduced role for hybrids. However, hybrids do still play a role due to use of biofuels. The doubling of biofuel share relative to 2030 levels reflects mitigation efforts towards biofuel production with CCS, allowing for negative emissions. Without such technologies, it is likely that the role of hydrogen and electric vehicles would be stronger in 2050.

3.3.3. Heating provision in buildings

Heating provision, which accounts for the largest share of energy demand in the building sector, is largely unaffected by system uncertainties. CO₂ prices deliver similar levels of heat pump uptake and district heating in both 2030 and 2050 across most simulations. The average space heating production reflects the profile observed in the deterministic run, with low standard deviations for any technology type (range of 5–15).

In part, this reflects the limited uncertainties accounted for in the buildings sector. In future analysis, many more uncertainties could be explored, also focusing on infrastructure build and demand side measures, not just technology costs. This could include uncertainty around the feasibility of district heating supply options, and investment cost implications e.g. decentralised versus centralised supply options, commercialisation of marine heat pumps and geothermal options, etc.

3.3.4. Biomass use

Highlighted in the sensitivity analysis, biomass availability is critical to meeting the 2050 target. This is evident by the much higher levels of biomass consumption in those simulations where the target is met (Fig. 9); average biomass use is 349 TWh compared to 195 TWh. The apparent impact of biomass resource availability is linked to its use in CCS technologies for power

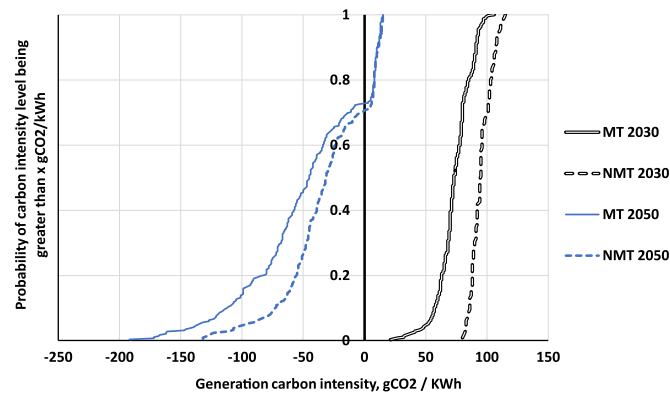


Fig. 6. Cumulative probability of carbon intensity of electricity in 2030 and 2050 in Sims meeting/not meeting target (MT/NMT).

production and biofuel production, and the model predisposition towards the use of biomass in CCS as a critical mitigation option in the longer term. In 2030, there is limited difference between the simulation cases.

4. Discussion

System wide uncertainty has a strong impact on the investment choices required to decarbonise the energy system in the mid to long term. Using a probabilistic energy systems modelling approach, the role of these uncertainties on achieving carbon targets has been explored. The results of the analysis highlight that the carbon price level is critical to ensuring decarbonisation is sufficient to deliver the UK's strategy objectives, and to mitigate this uncertainty.

In 2030, the level of carbon price is very sensitive; set too low (less £30/tCO₂) results in a low likelihood of achieving the required reduction levels. However, this risk can be mitigated by a relatively modest increase. In infrastructure planning terms, 2030 is not far off, and therefore incentive levels via a carbon price need to be carefully considered. Achieving the targets in the mid-term requires a lower carbon intensive generation mix, delivered by higher levels of nuclear, CCGT w/CCS, and other renewables, a lower carbon car vehicle fleet, notably through the higher uptake of hybrid vehicles and lower ICE vehicles in operation, and increasing levels of district heating provision and use of heat pumps for heat provision in buildings.

In the longer term (to 2050), uncertainties have a stronger impact on investment choices in both the power generation, fuel production and transport sectors. This results in fewer simulations (58%) meeting the target than observed in 2030, and a larger deviation from the target level. Incremental changes in carbon prices have a more limited impact on improving the probability of meeting the target level. While it is evident that policy makers do not need to determine incentive levels for investment for 2050 now, this analysis does show that the longer term strategy development does need to be cognisant of large uncertainties in the long term. If we consider our uncertainty focus in this analysis to be narrow, as argued later, this insight is even more critical.

A key uncertainty determining reduction levels in 2050 is the availability of biomass, ranked as very influential for both costs and emission metrics in the sensitivity analysis. Higher availability increases the probability of meeting the target, as the option to use biomass in CCS plant (either for power generation or biofuel production) is extremely attractive. Other key uncertainties for power generation are the price of gas and capital cost of nuclear. Both technologies contribute the most significant share of generation, although the relative contribution by and success in

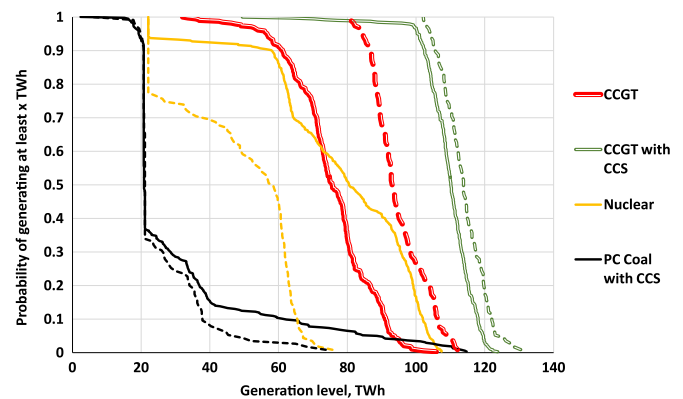


Fig. 7. Probability of electricity generation levels being at least at a specific level in 2030 in Sims meeting/not meeting target (dashed time series denote runs not meeting target).

meeting targets is dependent on these uncertainties. Given the sensitivity of the model to these three key uncertainties, our assumptions used merit further consideration.

The analysis also highlights a range of input uncertainties that do not impact on the model outputs. This includes a number of renewable technologies, which do not appear in many of the simulations. Based on an iterative analysis, these uncertainties could therefore be removed, narrowing the focus and complexity of the analysis.

5. Conclusions and policy implications

Developing strategy for deep decarbonisation of the energy system has to contend with pervasive and overlapping uncertainties. This paper highlights the impact of uncertainty on meeting reduction targets, and the importance of adequate price signals for ensuring investment in the low carbon energy system. It also highlights the importance of the electricity system in the transition, and the importance of key low carbon technologies, which strongly impact the cost of the transition as shown by sensitivity to gas price and nuclear capital costs. By 2050, target stringency steers system investment towards the use of CCS technologies with biomass. The predisposition to these technology types requires policy makers to further explore the uncertainties around biomass availability, and CCS technology availability.

The analysis presented in this paper could be extended. It is only the first stage of an iterative process between analyst and policy maker. Further discussion would help base the analysis in policy reality, and could be framed around the following

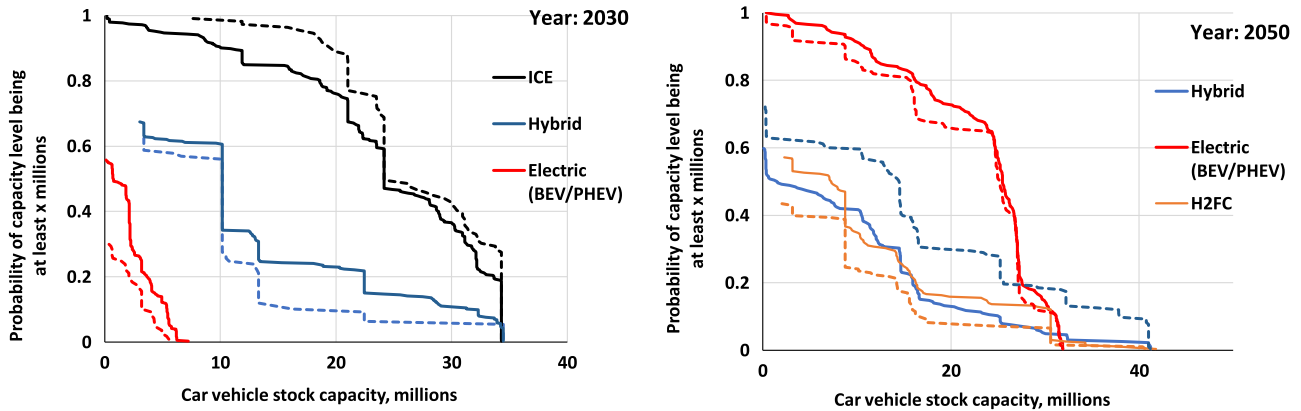


Fig. 8. Probability of car stock level by type being at least at a specific level in 2030 and 2050 in Sims meeting/not meeting target (dashed time series denote runs not meeting target).

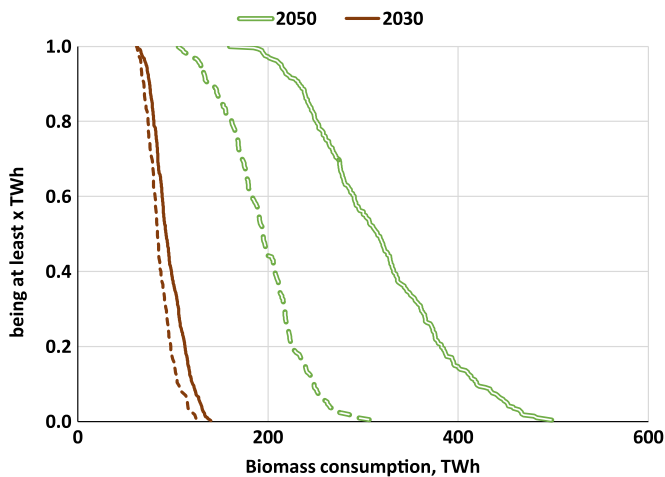


Fig. 9. Probability of biomass consumption being at least \times TWh in 2030 and 2050 reflecting uncertainty on resource availability (dashed time series denote runs not meeting target).

questions: (1) were all key parametric uncertainties introduced, and were the distribution used for those parameters sufficiently broad to capture all plausible futures? For example work to identify the nature, location and level of uncertainties through different approaches, such as expert elicitation (Usher and Strachan, 2013), model uncertainty characterisation or more systematic review of the literature, and (2) how does structural uncertainty impact on model outputs? Based on this discussion, (3) how do we adjust our analysis to either streamline, add or remove uncertainty?

We believe that this iterative process could significantly enhance strategy development. While not the same, it borrows two important concepts from long term planning analysis process set out by Lempert et al. (2003), that is to explore the many different plausible futures generated by the modelling, and iterate with the policy community in determining what matters.

There are a number of areas for developing this research, in addition to the iterative process proposed above. Firstly, a broader view of the uncertainty space could provide more insightful results. Our analysis, quite reasonably, focuses on commodity and technology cost and performance uncertainties; however, exploring broader uncertainties e.g. 'in-out' possibilities for technologies such biomass CCS, could be informative of the many different plausible futures. We argue that broadening the analysis of the uncertainty space is required in order to start discounting uncertainties that appear inconsequential in the model outputs. Secondly, further work is needed to elicit uncertainty distributions

for use in the modelling. Thirdly, exploration of structural uncertainty in the model is required. For example, it would be useful to understand why the buildings sector shows limited divergence from the deterministic pathway, or whether this reflects limited characterisation of the parametric uncertainties across this sector.⁵

In conclusion, this paper approaches the question of uncertainty using a probabilistic approach combined with sensitivity analysis. The strengths of this approach are apparent; it identifies (based on predefined uncertainties and model framework) the key assumptions that really matter, when ranked against all others. For policy, this additional understanding is fundamental to formulating strategies that recognise the key uncertainties, and their impact on achieving deep and sustained decarbonisation.

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Appendix A. Overview of model assumptions

This appendix provides an overview of updated model assumptions used in ESME v3.2. As part of the process of making the model more consistent with government assumptions, the following updates were made, and are further detailed in this appendix.

- Power sector costs (and learning), based on the latest estimates published by DECC (2013a).
- Transport sector costs and performance characteristics, used in recent CCC (2013) analysis (sourced primarily from AEA (2012), Element Energy (2013)).
- Fossil resource prices from the latest updated energy projections (UEP) publication (DECC, 2013b).
- Biomass prices based on information from E4tec (2012) and Redpoint (2012).
- Biomass resource availability estimates based on the bioenergy

⁵ There is a bias towards the power generation sector and transport sectors, which account for 75% of all uncertain inputs.

Table A1
Power sector CAPEX assumptions, £/kW.

Technology	2020	2030	2040	2050	2050 (Low)	2050 (High)	Uncertainty growth
PC coal	1338	1322	1305	1289	1115	1462	Low
PC coal with CCS	2347	2225	2092	1987	1367	2955	High
IGCC coal	2283	2257	2233	2218	1288	3149	Mid
IGCC coal with CCS	3511	3350	3198	3111	1209	4715	High
CCGT	610	601	593	587	451	736	Low
CCGT with CCS	1418	1330	1253	1201	574	1858	High
OCGT	438	433	429	425	246	443	Low
H2 turbine	747	724	701	654	326	982	Mid/high
Macro CHP	650	633	615	581	502	659	Low
Nuclear	4649	4310	3998	3763	2446	5765	Mid/high
Biomass fired generation	2530	2346	2180	2038	1168	2892	Mid
IGCC biomass with CCS	5726	5463	5216	5074	1638	8511	High
Incineration of waste	4900	4294	3780	3436	3058	3720	Low
Anaer. digestion gas plant	4180	4102	4032	3962	2300	6456	Mid
Anaer. digestion CHP plant	4200	4200	4200	4200	2438	6843	Mid
Oil fired generation	4870	4812	4749	4689	4057	5321	Low
Offshore wind	2570	2285	2034	1856	941	2836	Mid/high
Onshore wind	1500	1374	1259	1174	682	1544	Mid
Hydro power	3150	2908	2683	2496	2496	2496	Low
Tidal stream	3200	2878	2596	2389	1125	3400	High
Wave power	4610	3971	3430	3089	1478	3588	High
Tidal range	3000	2885	2775	2699	892	4506	Mid/high
Severn barrage	2330	2330	2330	2330	752	3908	High

*Uncertainty growth rates: Low – 1%, mid – 2.5%, Mid/high – 3.75%, High – 5%.

Table A2
Power sector O&M costs, £/kW.

Technology	Fixed O&M, £/kW/Yr				Variable O&M, £/KWh
	2020	2030	2040	2050	
PC coal	60.65	59.93	59.14	58.40	0.0190
PC coal with CCS	58.89	55.83	52.50	49.86	0.0020
IGCC coal	100.91	99.77	98.70	98.03	0.0016
IGCC coal with CCS	140.54	134.08	128.00	124.53	0.0020
CCGT	28.45	28.02	27.65	27.37	0.0001
CCGT with CCS	30.07	28.20	26.55	25.46	0.0020
OCGT	13.20	13.06	12.93	12.83	0.0001
H2 turbine	0.00	0.00	0.00	0.00	0.0000
Macro CHP	51.62	50.24	48.87	46.11	0.0001
Nuclear	70.59	65.44	60.70	57.13	0.0030
Biomass fired generation	83.86	77.75	72.26	67.54	0.0050
IGCC biomass with CCS	58.40	58.40	58.40	58.40	0.0010
Incineration of waste	179.49	171.24	163.49	159.05	0.0019
Anaer. digestion gas plant	183.30	160.62	141.38	128.55	0.0250
Anaer. digestion CHP plant	299.00	293.41	288.39	283.43	0.0300
Oil fired generation	372.70	372.70	372.70	372.70	0.0200
Offshore wind	0.00	0.00	0.00	0.00	0.0000
Onshore wind	89.24	79.35	70.62	64.44	0.0020
Hydro power	25.77	23.61	21.63	20.18	0.0000
Tidal stream	36.81	33.98	31.36	29.17	0.0100
Wave power	95.62	86.00	77.58	71.38	0.0010
Tidal range	79.13	68.17	58.88	53.03	0.0000
Severn barrage	36.58	35.18	33.84	32.92	0.0000

review by the CCC (2011).

Energy service demands were not updated; the ESME Reference

Table A3
Power sector build rate assumptions for key technologies, GW/Yr

Technology	2020	2030	2040	2050	2050 (low)	2050 (high)
CCS technologies	1	2	2	2	1.5	2.5
Nuclear	1	1	2	2	1.5	2.5
Onshore wind	1.5	1.5	1.5	1.5	1.125	1.875
Offshore wind	2	3	3	3	1.5	4.5

scenario was used, and is consistent with government demand projections from a range of models (as of April 2013), including the DECC energy model, and DfT transport demand models, including NTM. Key drivers underlying the demands include GDP growth estimates from the Office for Budget Responsibility (OBR, 2012) and population estimates from the Office for National statistics (ONS).⁶

Where presented, all cost data are expressed on a 2010 year basis.

Power sector

Power sector CAPEX assumptions are based on estimates in the main, with DECC and other international learning rates applied. High – low estimates are initially based on range values, for date of build (2020/2025);⁷ out to 2050, these uncertainties are assumed to grow by different rates, as highlighted in Table A1.

In the model, investments are annualised using a capital recovery factor (CRF) of 10% across all technologies. CCS retrofit technology cost assumptions in the model have been made consistent with the cost assumptions shown above. Operation and maintenance costs are listed in Table A2 below.

Build rates assumptions used in the model for key selected technologies are shown in Table A3.

Transport sector

Only car vehicle estimates have been updated in ESME, as the focus of the uncertainty analysis. Estimates for CAPEX (including uncertainty ranges) and fuel efficiency are from Element Energy (2013) and AEA (2012), and listed in Tables A4 and A5.

Resource prices and availability

Fossil fuel resource prices, shown in Table A6, are based on those used in the annual DECC UEP publication (DECC, 2013a, 2013b). The ranges specified are used to determine the uncertainty across prices. Domestic and imported biomass prices (and ranges) are based on estimates from E4tec (2012) and Redpoint (2012) analyses for Government.

The biomass availability range is based on the three scenarios considered in the CCC Bioenergy Review (2011), with biomass availability between 100 and 500 TWh, with 200 TWh as a central value.

Demand response

Price elasticity factors used in this analysis are shown in Table A7, and are from a paper by Pye et al. (2014a). Only the central estimates have been used, with demand response assumptions being held deterministic.

⁶ For population projections, ONS's 'low migration' variant is used, consistent with that used by the OBR in their forecasts.

⁷ To retain the uncertainty in these periods, the 2010 value is inflated. Inflated CAPEX costs for 2010 do not impact on model solution as there is no investment in 2010, as it is a historic period.

Table A4

Transport sector Car CAPEX assumptions, £/vehicles.

Vehicle type	Class	2020	2030	2040	2050	2050 (low)	2050 (high)
Car ICE	A/B segment	7581	8210	8696	8886	8998	8098
Car CNG	A/B segment	9258	10025	10619	10852	10987	9889
Car hybrid	A/B segment	9339	8866	8926	8951	8958	8063
Car PHEV	Short range A/B Seg	12554	10196	9980	9764	9548	8116
Car PHEV	Med range A/B Seg	13572	11022	10154	10086	10009	8507
Car PHEV	Long range A/B Seg	14590	11849	11359	10868	10378	8821
Car battery	A/B segment	18447	12524	9923	10056	10125	8100
Car hydrogen FCV	A/B segment	57351	23671	12727	11542	11242	8994
Car ICE	C/D segment	13673	14806	15283	15618	15813	14232
Car CNG	C/D segment	17695	19161	19779	20212	20465	18418
Car hybrid	C/D segment	16843	15990	15687	15730	15744	14170
Car PHEV	Short range C/D Seg	20483	16635	16426	16216	16007	13606
Car PHEV	Med range C/D Seg	22143	17984	16887	16775	16646	14149
Car PHEV	Long range C/D Seg	23804	19333	18686	18038	17391	14783
Car battery	C/D segment	30361	20613	18256	18502	18628	14902
Car hydrogen FCV	C/D segment	93326	37894	22030	19849	19298	15439

Table A5

Transport sector car efficiency assumptions, kWh/km.

Technology	Class	Fuel	2010	2020	2030	2040	2050
Car ICE	A/B segment	Liq. Fuel	0.56	0.46	0.38	0.33	0.31
Car CNG	A/B segment	Gas	0.67	0.55	0.45	0.40	0.37
Car hybrid	A/B segment	Liq. Fuel	0.43	0.37	0.32	0.29	0.27
Car PHEV	Short range A/B Seg	Liq. Fuel	0.31	0.23	0.19	0.17	0.15
Car PHEV	Med range A/B Seg	Liq. Fuel	0.21	0.15	0.13	0.11	0.10
Car PHEV	Long range A/B Seg	Liq. Fuel	0.10	0.08	0.06	0.06	0.05
Car battery	A/B segment	Elc.	0.14	0.11	0.10	0.10	0.09
Car hydrogen FCV	A/B segment	H2	0.17	0.14	0.13	0.12	0.12
Car ICE	C/D segment	Liq. Fuel	0.24	0.21	0.19	0.17	0.16
Car CNG	C/D segment	Gas	0.64	0.52	0.43	0.38	0.35
Car hybrid	C/D segment	Liq. Fuel	0.79	0.64	0.53	0.47	0.43
Car PHEV	Short range C/D Seg	Liq. Fuel	0.49	0.43	0.37	0.34	0.31
Car PHEV	Med range C/D Seg	Liq. Fuel	0.36	0.27	0.23	0.20	0.18
Car PHEV	Long range C/D Seg	Liq. Fuel	0.07	0.07	0.06	0.06	0.06
Car battery	A/B segment	Elc.	0.24	0.18	0.15	0.13	0.12
Car hydrogen FCV	A/B segment	H2	0.11	0.11	0.10	0.09	0.09
Car ICE	C/D segment	Liq. Fuel	0.15	0.14	0.13	0.12	0.12
Car CNG	C/D segment	Gas	0.19	0.18	0.16	0.15	0.14
Car hybrid	C/D segment	Liq. Fuel	0.30	0.26	0.23	0.22	0.20

*Activity per vehicle is 13533 km/y. For PHEVs, the efficiencies for both electricity and liquid fuel would be applied for each km, and represent the annual (fixed) ratio of fuels used.

Table A6

Resource price assumptions, p/kWh.

Resource	2010	2020	2030	2040	2050	2050 (low)	2050 (high)
Gas	1.53	2.52	2.52	2.52	2.52	1.44	3.60
Coal	0.87	1.10	1.10	1.10	1.10	0.83	1.48
Petrol	3.92	5.59	6.30	6.96	7.41	3.09	11.95
Diesel	4.29	6.11	6.90	7.62	8.11	3.38	13.09
Liquid fuel	4.11	5.85	6.60	7.29	7.76	3.23	12.52
Aviation fuel	3.36	4.79	5.40	5.96	6.35	2.65	10.24
Biomass	1.80	1.80	1.80	1.80	1.80	1.50	2.50
Biomass Imports	2.16	2.25	2.34	2.43	2.52	2.00	5.00

*Uranium and imported biofuel commodity prices have not been updated from those in v3.2.

Table A7

Elasticity input parameters by energy service demand.

ESD name	Sector	Low	Central	High
Aviation Domestic Passenger	Transport	-0.50	-0.70	-1.50
Aviation International Passenger	Transport	-0.40	-0.60	-1.00
Rail Passenger (electric and diesel)	Transport	-0.60	-0.80	-1.10
Rail Freight	Transport	-0.01	-0.03	-0.05
Road Passenger Car (2 size classes)	Transport	-0.15	-0.30	-0.50
Road Passenger Bus	Transport	-0.50	-0.70	-1.00
Road Freight Goods Vehicle (heavy and medium))	Transport	-0.05	-0.20	-0.30
Road Freight Light Goods Vehicle	Transport	-0.10	-0.25	-0.35
Maritime International Freight	Transport	-0.01	-0.03	-0.05
Maritime Domestic Freight	Transport	-0.01	-0.03	-0.05
Dwellings (3 density types – high, medium, low)	Residential	-0.10	-0.25	-0.40
Appliances	Residential	-0.05	-0.15	-0.30
Cooking	Residential	-0.05	-0.15	-0.30
Air Conditioning	Residential	-0.05	-0.15	-0.30
Commercial Floorspace	Comm./Public sector	-0.01	-0.10	-0.15
Public Floorspace	Comm./Public sector	-0.01	-0.10	-0.15
Industry (8 subsectors)	Industry	-0.01	-0.03	-0.05

References

- AEA, 2012. A Review of the Efficiency and Cost Assumptions for Road Transport Vehicles to 2050. Report Reference ED57444. April 2012. (<http://www.ricardo-aea.com/cms/assets/Documents-for-Insight-pages/8.-Review-of-cost-and-efficiency.pdf>).
- AEA, 2011. Pathways to 2050 – Key Results. A Report to the Department of Energy and Climate Change. May 2011. AEA, London. (https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48072/2290-pathways-to-2050-key-results.pdf).
- Biegler, Lorenz T., et al., 2011. Large-scale inverse problems and quantification of uncertainty. John Wiley and Sons, Chichester, UK, ISBN: 978-0-470-69743-6.
- CCC, 2013. Fourth Carbon Budget Review – Part 2: The Cost-Effective Path to the 2050 Target. Committee on Climate Change. December 2013. (<http://www.theccc.org.uk/>).
- CCC, 2011. Bioenergy Review. Committee on Climate Change. December 2011. (<http://www.theccc.org.uk/>).
- CCC, 2010. The Fourth Carbon Budget – Reducing Emissions through the 2020s. Committee on Climate Change. December 2010. (<http://www.theccc.org.uk/>).
- CCC, 2008. Building a Low-Carbon Economy – the UK's Contribution to Tackling Climate Change. Committee on Climate Change, London.
- Chaudry, M., Abeysekera, M., Hosseini, S., Wu, J., Jenkins N., 2014 UKERC Energy Strategy Under Uncertainties: Uncertainties in UK Heat Infrastructure Development, UKERC Working Paper UKERC/WP/FG/2014/005, May 2014.
- Davies, G., Prpich G, Strachan N and Pollard, S (2014), UKERC Energy Strategy Under Uncertainties: Identifying Techniques for Managing Uncertainty in the Energy Sector. UKERC Working Paper UKERC/WP/FG/2014/001, April 2014.
- DECC, 2013a. Electricity Generation Costs. Department of Energy and Climate

- Change (December 2013).
- DECC, 2013b. Updated Energy and Emission Projections 2013, September 2013. (https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/239937/uep_2013.pdf).
- DECC, 2011. The Carbon Plan: Delivering our Low Carbon Future. Department of Energy and Climate Change (December 2011).
- DECC, 2009. Carbon Valuation in UK Policy Appraisal: A Revised Approach. Climate Change Economics, Department of Energy and Climate Change (July 2009).
- DTI, 2003. Options for a Low Carbon Future. DTI Economics Paper No. 4. Department for Trade and Industry, June 2003. (<http://www.dti.gov.uk/files/file14769.pdf>).
- E4tec, 2012. Technology Innovation Needs Assessment (TINA) Bioenergy Summary report. On behalf of Low Carbon Innovation Coordination Group, Carbon Trust. (<http://www.carbontrust.com/media/190038/tina-bioenergy-summary-report.pdf>).
- Ekins, P., Anandarajah, G., Strachan, N., 2011. Towards a low-carbon economy: scenarios and policies for the UK. *Clim. Policy* 11 (2), 865–882.
- Element Energy, 2013. Pathways to High Penetration of Electric Vehicles. December 2013. (http://www.theccc.org.uk/wp-content/uploads/2013/12/CCC-EV-pathways_FINAL-REPORT_17-12-13-Final.pdf).
- Emhjellen, K., Emhjellen, M., Osmundsen, P., 2002. Investment cost estimates and investment decisions. *Energy Policy* 30 (2), 91–96.
- Funtowicz, S.O., Ravetz, J.R., 1990. Uncertainty and Quality in Science for Policy, vol. 15. Springer Science & Business Media, ISBN: 9780792307990, Kluwer Academic Publishers, the Netherlands.
- Heaton, C., 2014. Modelling Low-Carbon Energy System Designs with the ETI ESME Model. Energy Technologies Institute.
- HMG, 2008. The Climate Change Act. HMSO, London (Available at).
- HMT, 2003. The Green Book: Appraisal and Evaluation in Central Government. Treasury Guidance. The Stationary Office (TSO), London.
- Hourcade, J.C., Jaccard, M., Bataille, C., Gherzi, F., 2006. Hybrid Modeling: New Answers to Old Challenges. *Energy J.* 2 (Special issue), 1–12.
- Huntington, H.G., Weyant, J.P., Sweeney, J.L., 1982. Modeling for insights, not numbers: the experiences of the energy modeling forum. *Omega* 10 (5), 449–462.
- Hygh, J.S., DeCarolis, J.F., Hill, D.B., Ranji Ranjithan, S., 2012. Multivariate regression as an energy assessment tool in early building design. *Build. Environ.* 57, 165–175.
- IPCC, 2014. Summary for Policymakers. In: Edenhofer, O., Pichs-Madruga, R., Sokona, Y., Farahani, E., Kadner, S., Seyboth, K., Adler, A., Baum, I., Brunner, S., Eickemeier, P., Kriemann, B., Savolainen, J., Schlömer, S., von Stechow, C., Zwickel, T., Minx, J.C. (Eds.), *Climate Change 2014, Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.
- Jebaraj, S., Iniyar, S., 2006. A review of energy models. *Renew. Sustain. Energy Rev.* 10 (4), 281–311.
- Kann, A., Weyant, J.P., 2000. Approaches for performing uncertainty analysis in large-scale energy/economic policy models. *Environ. Model. Assess.* 5 (1), 29–46.
- Keirstead, J., Shah, N. (Eds.), 2013. *Urban Energy Systems: an Integrated Approach*. Routledge, Oxford, UK.
- Lempert, R., Popper, S., Bankes, S.C., 2003. *Shaping the Next one Hundred Year – New Methods for Quantitative Long-Term Policy Analysis*. RAND, Santa Monica, CA. (ISBN 0-8330-3275-5).
- Loulou, R., Remme, U., Kanudia, A., Lehtila, A., Goldstein, G., 2005. Documentation for the TIMES Model. Energy Technology Systems Analysis Programme (ETSAP) (April 2005).
- Morgan, M.G., Small, M., 1992. *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge University Press, Cambridge, UK.
- OBR, 2012. Fiscal Sustainability Report. Office for Budget Responsibility. HMSO, ISBN: 9780108511844 (July 2012).
- Pfenninger, S., Hawkes, A., Keirstead, J., 2014. Energy systems modeling for twenty-first century energy challenges. *Renew. Sustain. Energy Rev.* 33, 74–86.
- Pye, S., Usher, W., Strachan, N., 2014a. The uncertain but critical role of demand reduction in meeting long-term energy decarbonisation targets. *Energy Policy* 73, 575–586.
- Pye, S., Sabio, N., Strachan, N., 2014b. Energy Strategies Under Uncertainty: An Integrated Systematic Analysis of Uncertainties in UK Energy Transition Pathways. UK Energy Research Centre <http://www.ukerc.ac.uk/> (UKERC Report UKERC/WP/FG/2014/002).
- Redpoint (2012). Assessment of the Appropriate Uses of Bioenergy Feedstocks in the UK Energy Market. Final Report for the UK Department of Energy and Climate Change, and the Committee on Climate Change. April 2012. (https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/48340/5128-assessment-of-the-appropriate-uses-of-bioenergy-fe.pdf).
- Risbey, J., van der Sluijs, J., Klopogge, P., Ravetz, J., Funtowicz, S., Quintana, S.C., 2005. Application of a checklist for quality assistance in environmental modelling to an energy model. *Environ. Model. Assess.* 10 (1), 63–79.
- Saltelli, A., Ratto, M., Andres, T., Campolongo, F., Cariboni, J., Gatelli, D., Saisana, M., Tarantola, S., 2008. *Global sensitivity analysis*. John Wiley and Sons, Chichester, England.
- Saltelli, A., Annoni, P., 2010. How to avoid a perfunctory sensitivity analysis. *Environ. Model. Softw.* 25, 1508–1517.
- Strachan, N., Pye, S., Kannan, R., 2009. The iterative contribution and relevance of modelling to UK energy policy. *Energy Policy* 37 (3), 850–860.
- Usher, W., Strachan, N., 2013. An expert elicitation of climate, energy and economic uncertainties. *Energy Policy* 61, 811–821.
- Usher, W., Strachan, N., 2012. Critical mid-term uncertainties in long-term decarbonisation pathways. *Energy Policy* 41, 433–444.
- van Vuuren, D.P., Weyant, J., de la Chesnaye, F., 2006. Multi-gas scenarios to stabilize radiative forcing. *Energy Econ.* 28 (1), 102–120.
- Watson, J., Gross, R., Ketsopoulou, I. and Winskel, M., 2014. UK Energy Strategies Under Uncertainty-Synthesis Report, UKERC Ref UKERC/RR/FG/2014/002, London).