UKERC Energy Strategy Under Uncertainties

An Integrated Systematic Analysis of Uncertainties in UK Energy Transition Pathways

Working Paper

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UKERC is undertaking two flagship projects to draw together research undertaken during Phase II of the programme. This working paper is an output of the Energy Strategy under Uncertainty flagship project which aims:

- To generate, synthesise and communicate evidence about the range and nature of the risks and uncertainties facing UK energy policy and the achievement of its goals relating to climate change, energy security and affordability.
- To identify, using rigorous methods, strategies for mitigating risks and managing uncertainties for both public policymakers and private sector strategists.

The project includes five work streams: i) Conceptual framing, modelling and communication, ii) Energy supply and network infrastructure, iii) Energy demand, iv) Environment and resources and v) Empirical synthesis. This working paper is part of the output from the Environment and resources work stream.

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Acknowledgements

The authors would like to acknowledge the input from the team at ETI, led by Chris Heaton, who have provided additional information on input assumptions and further guidance on the use of ESME. It is important to note that in this analysis we are using quite a distinctive version of ESME from the standard v3.2 release, and therefore these results should in no way be attributed to the ETI.

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Summary

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, and exist in a strategic policy area where the impact of investment decisions have long term consequences. Uncertainty also lies in the tools and approaches used, increasing the challenges of informing robust decision making. Energy system studies in the UK have tended not to address uncertainty in a systematic manner, relying on simple scenario or sensitivity analysis. This paper utilises an innovative 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 global sensitivity analysis is then undertaken to explore the uncertainties that have most impact in the long term mitigation pathways.

The analysis highlights the strong impact of uncertainty on delivering the required emission reductions under a given carbon price. In the mid-term (2030), the likelihood of meeting legislated reduction targets is extremely sensitive to the carbon price level, with a modest reduction or increase in carbon pricing leading to the target being or not being met. The uncertainty in the carbon price level for achieving emissions mitigation increases further in the longer term (2050). The cost and availability of a range of technologies is key in delivering required reductions; in the mid-term, decarbonisation of the power sector is critical, with cost-effective nuclear and CCS technologies playing a vital role. In the longer term, the availability of biomass for use in CCS technologies (power and biofuel production) along with the cost of nuclear technologies and gas prices play a critical role in delivering emission reductions.

Further iteration of this energy systems uncertainty analysis is needed with policy makers and stakeholders around the role of uncertainties. Key questions include whether these uncertainty impacts are likely to play out in reality or are a function of the modelling, and the scope of the uncertainty analysis i.e. what is missing and what else is needed. Such iteration allows us to determine the robustness and relevance of the insights emerging from this analysis for informing future UK low carbon transitions.

1 Introduction

1.1 Context

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 a 50gCO_2/kWh by 2030 could be of the order of £200 billion between 2014 and 2030.

The issue of uncertainty is recognised by DECC (2011) in the UK low carbon strategy (The Carbon Plan) and by CCC (2013) in their guidance. The CCC note key sensitivities across drivers of emissions (GDP, population) and in relation to cost and uptake of key technologies (including power generation intensity, heat pumps, and electric vehicles). Uncertainties around these specific technologies are critical because in large part they ensure delivery of carbon budgets and the 2050 target, in a cost-effective manner.

1.2 Research aims

The objective of the analysis presented in this working paper is to explore the impact of technology uncertainties critical to delivery of a lower carbon energy system, using the energy systems model, ESME (see section 3.1). This model provides a framework for systematic analysis of multiple uncertainties, using a probabilistic approach, on target delivery and technology pathways out to 2050. The focus of uncertainties is on the cost and uptake of key technologies, crucial for mitigation action in the mid-term, and necessary to meet the longer term 2050 target. Specifically, we consider the following issues –

- The likelihood of meeting or missing emission reduction targets under a given set of carbon prices.
- The sensitivity of carbon price level, and impact on meeting targets.
- Where reduction targets are met, the combination of technologies and fuels that are most prevalent. This highlights those technologies that are most critical for meeting targets.
- Through sensitivity analysis, identifying the uncertainties that have most impact on target delivery.

Understanding the impact of uncertainty on the system is critical for policymaking. It can assist in identifying what uncertainties matter and how these can best be mitigated. For example, it might be prudent to consider higher carbon price signals to ensure incentives are at a level that mitigates uncertainty around costs of key technologies in the longer term. It can also provide insights into where R&D focus may be needed for a critical technology, again to mitigate future uncertainty. In the UK energy and climate policy area, there is increasing recognition of the importance of characterising uncertainties and their impact on a low carbon transition, and this wider UKERC research provides a timely contribution to the debate.

1.3 Paper layout

The paper is structured as follows; section 2 provides a brief overview of uncertainty assessment in energy system models, including use of uncertainty approaches in UK modelling analyses, types of relevant approaches to uncertainty assessment and selection of appropriate techniques. The paper then proceeds to describe our approach to the analysis in section 3, including a description of the ESME model, and its set-up for this analysis, including data assumptions used. Results of modelling are then presented in section 4, highlighting the impact of key uncertainties on the decarbonisation pathway. Finally, the key insights are described in section 5, and what these mean for policy.

2. Modelling uncertainty in energy systems analysis

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 did not address 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. A recent UKERC report seeks to address the problem described in ii) by undertaking a comparative analysis of scenarios output from policy relevant systems modelling studies (Ekins et al. 2013).

The many uncertainties associated with energy system transition under stringent mitigation targets necessitate a more robust approach to modelling uncertainty. Usher and Strachan (2012) used a two-stage stochastic version of the UK MARKAL model, focusing on mid-term uncertainties associated with fossil fuel price and biomass availability. The potential limitation of this approach is the small number of uncertainties that can be considered due the limits required to ensure the analysis is computationally tractable.

In considering the different approaches to uncertainty analysis, how we characterise uncertainties is critical to the type of approach we adopt. One way to characterise uncertainties is in respect of their level, location and nature (Skinner et al. 2013). *Level* concerns the impact of uncertainties in decision making. Davies et al. (2014) present a graphic representation of the decision levels as a function of the system uncertainties, where operational, strategic/tactical and policy levels can be represented, building on the framework proposed by Functowicz and Ravetz (1990). *Location* concerns uncertainty being in the model input parameters or structure (Bauer et al. 2010). *Nature* concerns the potentially controllable nature, as epistemic or its completely random essence, as aleatory (Beven 2010).

It could be argued that energy system uncertainties fall into questions of 'policy' (termed 'post-normal science' in Functowicz 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 made 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.

Keirstead and Shah (2013) further 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.

The type of probabilistic uncertainty approach used in this paper is often used where both system uncertainties and decision stakes are high. This stochastic technique is used to propagate the probabilistic knowledge on uncertainty in the inputs throughout the model resolution. It is widely used due to its advantages in using knowledge about the probabilistic nature of inputs and its flexibility in the formulation to represent the deterministic counterpart problem. Disadvantages of the approach lie in the difficulty of finding probabilistic data for the inputs and in the fact of assuming probability distributions and parameters to be invariant in the model once they are set. In their conceptual paper for determining uncertainty approaches to use, Davies et al. (2014) propose that such an approach is positioned on the boundary of strategic and policy decision making (or post-normal science space), and therefore is an appropriate technique to use for uncertainty analysis of the energy system.

Figure 1 shows the uncertainty analysis framework used in this paper.

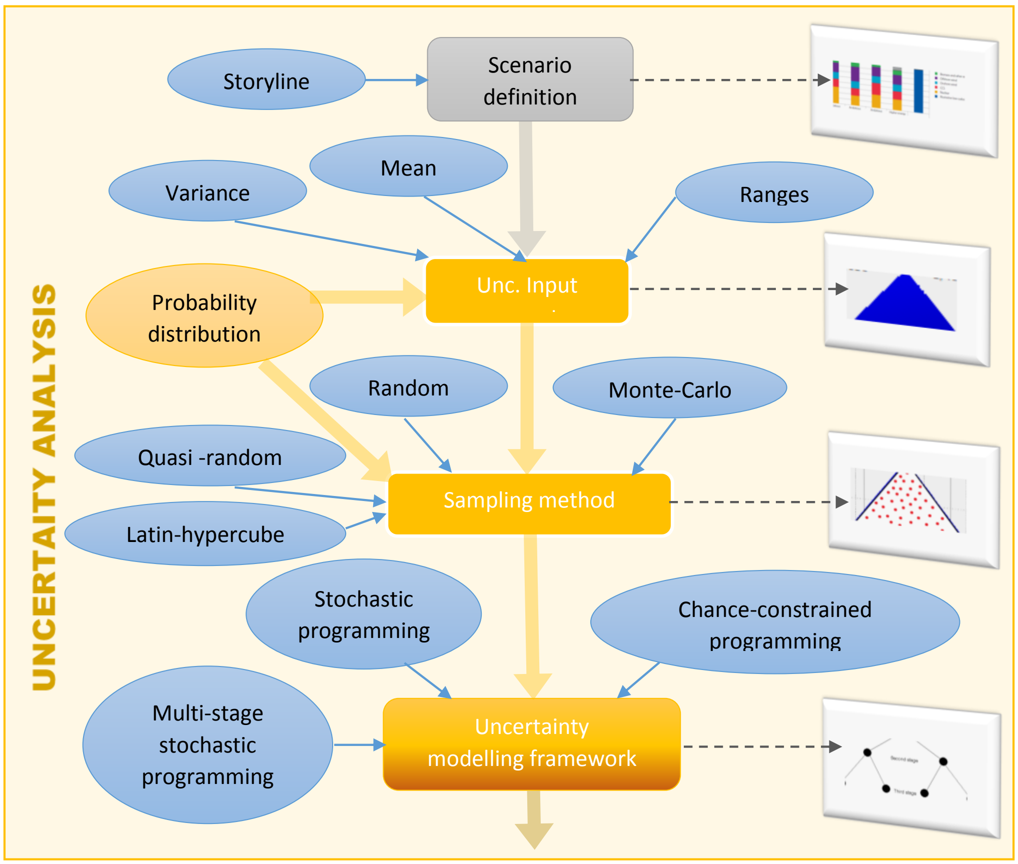


Figure 1. Uncertainty analysis framework[1]

When it comes to analysing the impact of uncertainty in the model output, sensitivity analysis helps determine robust conclusions based on uncertain model results. In general, sensitivity analysis techniques can be relatively complex if done properly, but it is common in the literature to find studies that analyse the sensitivity of the results to one or two input parameters at most. The aim of a sensitivity analysis here is to analyse at the same time the effects that all the uncertain input parameters have in the model

[1] This figure does not represent a complete classification of uncertainty analysis methodologies. See Davies et al. 2014 for additional information on this topic.

output. Figure 2 shows a schematic representation of the sensitivity analysis methodologies explored.

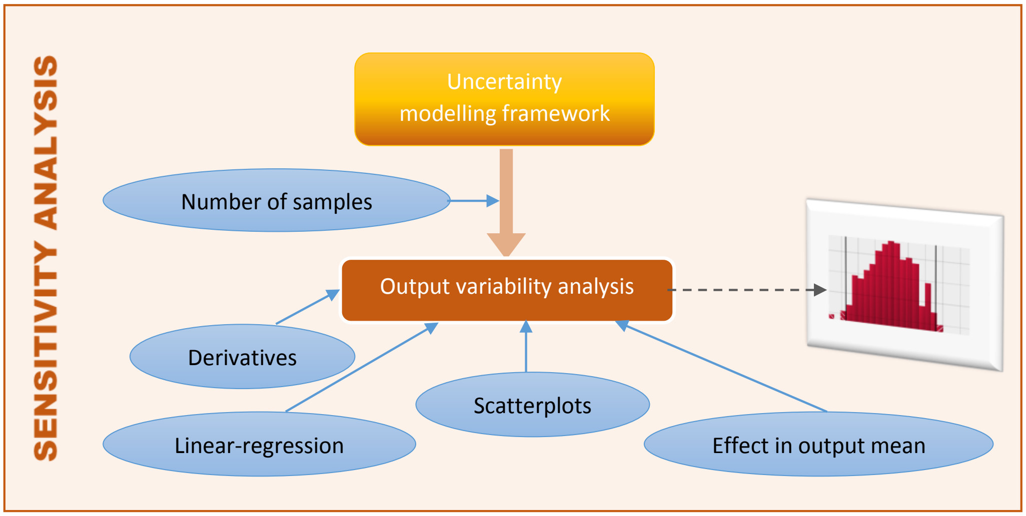


Figure 2. Global sensitivity analysis framework[2]

The aim of this work to combine the advantages of exploring uncertainties in the model using a probabilistic approach and combining it with an integrated systematic sensitivity analysis to explore the effects of the uncertain model parameters in the model output. Following the guidance and setting types described by Saltelli et al. (2008) we first define the goal of our sensitivity analysis, which is to identify key uncertainties that lead to maximum likelihood of not meeting the UK carbon targets. This means the following sensitivity analysis settings are relevant for our work – 1) *Factor prioritization*, 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.

3 Methodology

Our approach uses the ESME model to assess the impact of uncertainty across key technologies considered critical for meeting the 4th Carbon Budget, and longer term 2050 target. This has been done by running the model probabilistically, using a notional set of carbon prices observed to deliver the emission reduction targets under a wholly deterministic run in ESME. The probabilistic approach, using Monte Carlo simulations, allows for investigation into the delivery of carbon targets under uncertainty, and differences in the type of technology pathways. In addition, by varying the carbon price

[2] This figure does not represent a complete classification of uncertainty analysis methodologies. See Saltelli et al. 2008 for information on this topic.

(via sensitivity runs), the opportunities for increasing or reducing the likelihood of missing future targets can also be explored.

3.1 ESME overview

ESME (Energy Systems Modelling Environment), 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. ESME analysis has also been used by UK Department for Energy and Climate Change (DECC) and the UK Committee on Climate Change (CCC) to inform strategy development and advice (CCC 2011, CCC 2013, DECC 2011).

Built in the AIMMS environment, ESME uses linear programming to assess cost-optimal technology portfolios. The mathematical programme is similar to that used in other bottom-up, optimisation model, such as MARKAL-TIMES (Loulou et al. 2005), where the objective function is to maximise total economic surplus, subject to constraints.[3] A key feature differentiating ESME from other models is that uncertainty around cost and performance of different technologies and resource prices is captured via a probabilistic approach, using Monte Carlo sampling techniques. The focus of uncertainty in ESME has focused on (although is not restricted to) technology investment costs in the power, buildings and transport sectors, fuel costs and resource potential e.g. biomass imports.
For this analysis, v3.2 of the model has been used in conjunction with a recently developed elastic demand extension. A description of the price elasticity assumptions can be found in Appendix 1. In addition, a range of assumptions used in v3.2 of the model have been changed for this analysis, and are described in the next section.

3.2 Modelling a deterministic reference pathway

The first step in our approach is to ensure that the model is increasingly aligned to assumptions underpinning the 4th Carbon Budget review (CCC 2013). This is important as this forms the reference point from which to explore uncertainty, and the level of carbon price necessary to deliver UK mitigation goals. This deterministic pathway is aligned to the following extent –

- It uses a consistent set of emission targets out to 2050, as per those set out in the 4th Carbon Budget review report.
- It includes some known policies, specifically the 2020 RE target.

[3] This is the objective function where consumer surplus gains / losses associated with demand response are captured. In the standard version with no demand response, the objective function is the minimisation of total system costs.

- It uses a set of revised assumptions consistent with those used by DECC / CCC for those technologies / commodities which are of most interest in respect of system uncertainties, and the delivery of carbon targets.

The resulting deterministic pathway does not however mirror what is presented in the CCC analysis, and that is not the intention. The ESME model uses an optimisation framework, is run in relatively coarse time steps and does not capture some of the nuances in the CCC analysis. However, this pathway does provide a reference point for exploring some of the uncertainties around key mitigation options.

In summary, the following model revisions were made to ESME v3.2 assumptions (current and projected) –

- 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 review by the CCC (2011b).

A detailed description of these updates can be found in Appendix 1. All other technology assumptions are based on ETI analysis, and consistent with those found in version 3.2 of the model. Concerning energy service demands, the ETI's *Reference scenario* has been used in this analysis, 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).[4]

Key time series outputs for the deterministic pathway are presented in Figure 3 for power generation, vehicle stock, and building space heating. The 2030 generation profile has a higher carbon intensity (89 gCO_2/KWh) than observed in the CCC cost-effective pathway (50 gCO_2/KWh), with less low carbon capacity (50 GW) and higher load factors for gas CCGT. For the power sector, this pathway delivers an 80% reduction on 2010 levels, compared to 88% in the CCC analysis. Out to 2050, the role of gas

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

continues due to increased build of CCGT w/CCS (40 GW in 2050), while nuclear capacity grows significantly, at 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). The key difference is the much 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% in the ESME analysis, relative to 2010 levels. This reduction is larger than in the CCC analysis, and reflect a more optimistic view concerning the penetration of district heating, providing significantly more than the 6% of heating demand in the CCC analysis. A 39% reduction in industry sector emissions is in line with the CCC analysis.

This reference pathway run determines a set of carbon prices necessary for delivering carbon reduction targets, based on the assumptions in the model (Table 1). They reflect the marginal costs of domestic mitigation, given the representation of the energy system, and the different technology and resource constraints. They are in the range of estimates observed in other energy system modelling studies (AEA 2011).[5]

Table 1 Carbon prices (undiscounted) under deterministic reference pathway

	2020	2030	2040	2050
Carbon price (£2010/tCO_2)	13	133	226	421

[5] 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.

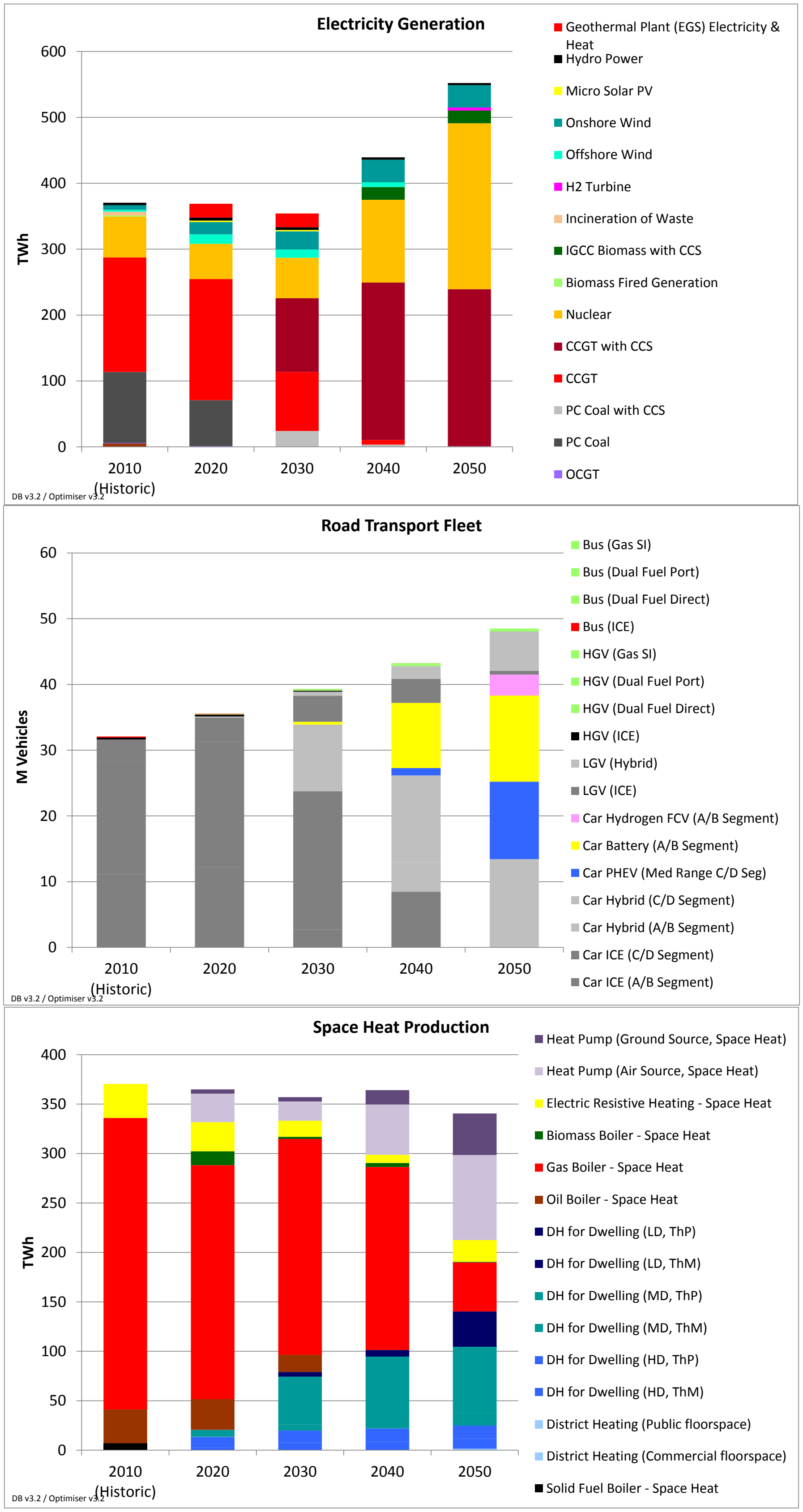


Figure 3 Key output results from Reference pathway in ESME

To determine the focus of the uncertainty analysis using ESME, we first engaged with UKERC colleagues working on different work streams of the wider UKERC uncertainties project (Watson 2014). This process was extremely useful at identifying key uncertainties that could be considered (or not) in the modelling. The CCC (2013) analysis also highlights key uncertainties, guided by the emergence of critical technologies and fuels underpinning the pathway, and was also important in providing the focus for uncertainty analysis.

The process of uncertainty analysis in this work is presented in Table 2 and was carried out following the generic steps depicted in Figure 1.

Table 2 Uncertainty analysis steps

Step	Description	Source
Scenario definition	CCC Updated 4th Carbon Budget	CCC (2013)
Uncertain input selection	Based on expert consultation	See Table 3
Uncertain input data	Based on available literature	See Table 3 and Appendix 1
Uncertain input probability distribution	Triangular(min, mode, max)	Biegler et al (2011), Emhjellen et al (2002)
Sampling method	Monte Carlo sampling	ETI (as used in ESME v.3.2)

Table 3 lists the input assumptions that were characterised as uncertain, and used in the Monte Carlo simulations. All other input assumptions in the model are held deterministic. The source of uncertainty data was primarily based on ranges found in the literature, also provided in Table 3. The range values can be found in Appendix 1.

Table 3 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 2014), DH from ETI (as used in ESME v3.2)
Resource availability – biomass	Max annual availability of biomass (incl. imports)	CCC (2011b). Bioenergy review.
Resource prices	Including fossil fuels and biomass	DECC (2013b) for fossil fuels. E4tec (2012) and Redpoint (2012) for biomass.

Using the above sources to estimate ranges of uncertainty provides a starting point at which to develop probability distribution functions. Given the lack of available data on future uncertainties, a compromise has been 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. As discussed in our conclusions, further work is needed to identify the nature, location and level of uncertainties through different approaches, such as expert elicitation, model uncertainty characterisation or more systematic review of the literature. Usher and Strachan (2013) addressed the problem of lack of data through expert elicitation; however, their method of choosing uncertainties on which to focus was ultimately based on expert judgement.

3.4 Running model simulations

Monte Carlo simulations were used to propagate the probability distributions on input assumptions through the model, under the carbon prices described in section 3.2. It is important to note two features of the sampling routine. Firstly, only 2050 values are sampled. The distribution of 2050 values is cascaded back to earlier years, using indices. The approach is taken for two reasons – data management and to ensure consistency between periods for a given simulation (e.g. lower costs in 2020 (relative to 2010) for technology X are not followed by high costs in 2030, for a given simulation). As all indices start at 1 in 2010, this results in decreasing uncertainty the earlier in the time horizon. Indices can of course be 'shaped' to ensure uncertainties are not too low in the near term.

Figure 2 shows investment costs for onshore wind. The black line shows the deterministic cost assumptions over time. When running Monte Carlo simulations, only the 2050 value is sampled, and then indexed back, using the shape of the index. This is illustrated for two sample points labelled 'low' and 'high'. Secondly, some of the distributions are correlated to ensure consistency within technology groups. This avoids, for any given simulation, inconsistencies such as very high costs for CCS power technology A and very low costs for CCS power technology B.

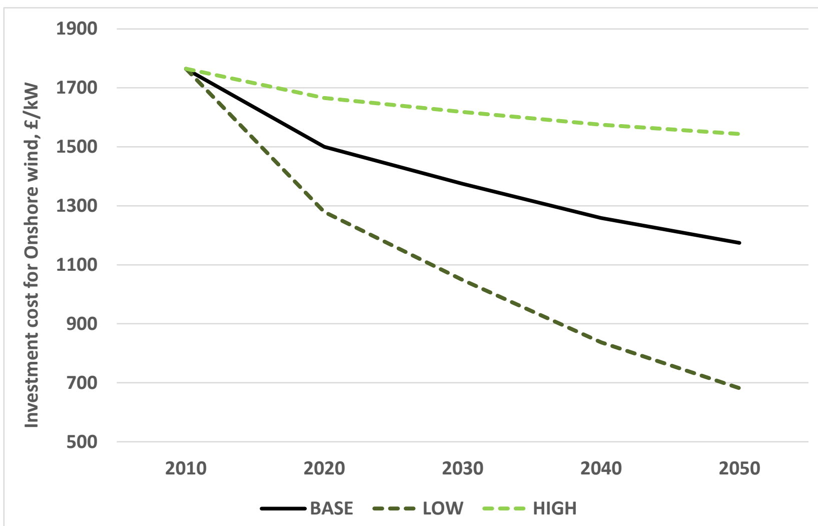


Figure 4 Indices for estimating pre-2050 simulated values

The number of model runs that adequately cover the uncertainty space were estimated based on Equation 1, introduced by Morgan et al. (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.[6]

$$n > \left(\frac{2cs}{w£}\right)^2 \qquad (1)$$

Where c is the deviation enclosing 95% of the probability, s is the standard deviation of the sample and w is the width of the interval desired (see Table 4).

[6] For ease of analysis, a sample size of 500 was used.

Table 4 Estimation of sample size for Monte Carlo analysis

Parameter	Description	Value	Unit
c	Deviation enclosing 95% of the probability	~2	–
s	Standard deviation of the sample	$7.41 \cdot 10^9$	£
W	Interval width to estimate the mean with less than 1% coefficient of variation	$2.63 \cdot 10^9$	£
N	Number of model runs required	475	
T	Resolution time for one model run[7]	5–10	Minutes

The model is then run for 500 simulations, propagating the sampled values through each simulation. As demand response is also being characterised in this analysis, each simulation requires a calibration run to determine demand curves, increasing the model run number to 1000. The model is run in 10 year periods, for a time horizon of 2010 to 2050. A discount factor of 3.5% is used, 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.

3.5 Analysing the impact of uncertainty in the output variability

As introduced by Saltelli et al. (2010), regression techniques are a straightforward way to carry out a global sensitivity analysis. The main goal of the sensitivity analysis in the context of this report is to explore the influence of the input uncertainties on key model outputs (in ESME, total system cost and total emissions).

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 standardized regression coefficients (SRC) 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 et al., 1992). The main advantages of using SRC as an uncertainty important 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.

[7] The computer used is an Intel inside core i7 processor with 16GB RAM memory.

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 models for 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 standardized regression coefficients were used as a sensitivity measure to determine the importance of the design parameters in the building energy consumption.

The sensitivity analysis performed in this work is comprised of two main steps:

1. Graphical analysis using scatterplots. The correlation of each uncertain input with the output variable of interest can be initially investigated using scatterplots. Although plotting the scatterplots of each input data against the outputs can still be useful, marginal differences between different factors can be difficult to differentiate.

2. Multivariate linear regression (MVLG). 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 SRC, 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.

The sensitivity analysis performed has an iterative nature and once 1) and 2) are performed and compared to unveil potential discrepancies, results can then be presented to policy relevant stakeholders for further scrutiny. The intention of this analysis is for the inputs with higher values of SRC to be considered for further analysis and variation and for the inputs with the lowest SRC to be considered as deterministic in further analysis.

Although SRC is a useful sensitivity metric, it should be noted that it is only available to capture first order interactions within the model. This means that quadratic or higher order effects cannot be captured using this metric. In this sense, Saltelli et al. (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 non-linearity of the model by means of the model coefficient of determination R^2. In this sense, the fact that ESME is originally a linear programming model already indicates the appropriateness for the use of this metrics, while avoiding to take unnecessarily more complicated steps.

The regression model obtained for each of the output variables under analysis follows a generic linear form as expressed in Equation 2:

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

Where i represent the 500 Monte Carlo samples obtained for each of the z_j uncertain parameters in in our analysis (see Appendix 1), b_0 is the constant of the regression model and b_{Zj} are the regression coefficients.

Each sub-model has a specific value of R^2 which informs of the linearity of the original model. Equation 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_N are the original model coefficients and y_N are the output obtained with ESME model.

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

The ESME model is resolved so that the total system cost is minimised, while emissions are disincentivised using carbon prices in each of the time periods defined. In the model, constraints relate the variables and model parameters in different ways, and therefore correlate them. Although most of the model variables are correlated, either through the model constraints or through specified correlation coefficients in the sampling experiment, we assume that we do not have any information *a priori* of the relationships between variables. Therefore, we perform our sensitivity analysis to uncover the relationships between the model inputs and between the inputs and the output variables (in this case, total system costs and total emissions).

Figure 5 shows a schematic representation of a linear program with an objective function and two constraints. The uncertainty analysis using Monte Carlo sampling provides points for analysis for x_1 and x_2 under the shaded area, and the sensitivity analysis aims at understanding the importance of the variation of x_1 and x_2 on the output y, which is represented by the arrows.

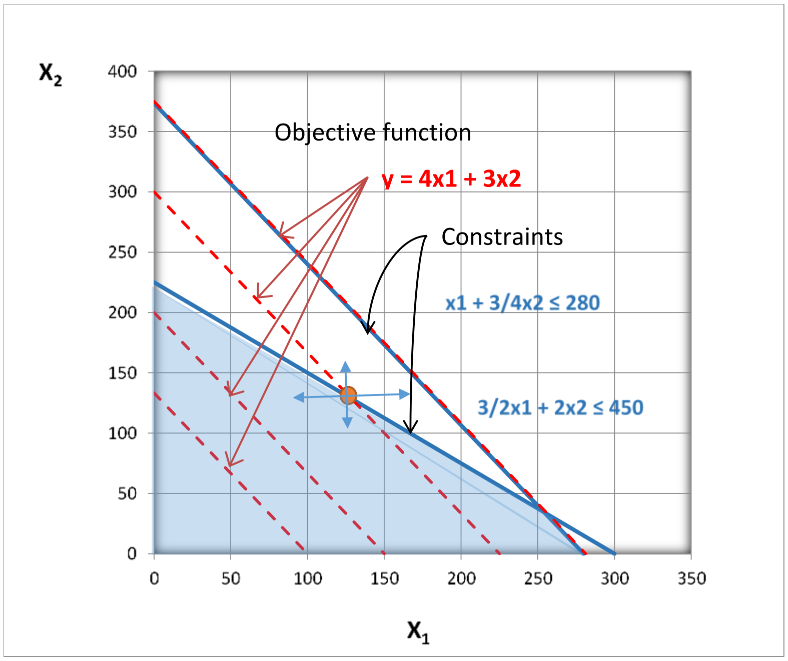


Figure 5. Schematic representation of linear program example

For the special case of a linear model, Saltelli et al. (2008) demonstrate that sigma normalized derivatives are equivalent to SRCs. In this sense, as our model is linear (as highlighted later), we can conclude that SRC will provide a good approximation of the real first order sensitivity indices on the basis of which we will rank the uncertain parameters by their impact on the outputs analysed. 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 is 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 Equation 2 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.

4 Results

4.1 Meeting targets under uncertainty

A key objective of this analysis was to consider the impact of uncertainty on meeting emission reduction targets. As described earlier, this was modelled by running the model under a set of carbon prices, in effect placing a carbon tax on each tonne of CO_2, and exploring whether or not the emission reduction levels necessary to meet future reduction targets were achieved. Carbon prices in this sense are being used as a proxy target, and this analysis is therefore not seeking to provide insights on a carbon tax policy per se. The carbon prices used were first derived by running the model deterministically, under the emission reduction targets to meet the 4th Carbon Budget and longer term 2050 target. Our results focus is therefore on the 2030 and 2050 periods.

Under this analysis, the likelihood of meeting or not meeting targets can be observed in Figure 6, and is based on the number of model simulations that either exceed the target level or not across the model years. The probability of missing the target 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%. However, in 2030 the percentage deviation from the target level is small, with the target level never exceeding 5% while in 2050, the deviation is much larger. However, some care is needed in interpreting these differences from the target level; a 5% deviation in 2030 is equivalent to 14.3 $MtCO_2$, while in 2050 it would equate to 5.25 $MtCO_2$.

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. As discussed previously, the assumptions around the temporal dimension of uncertainty is crucial to the model outputs, and arguably our uncertainty distributions are too conservative in 2030 (as discussed later in the conclusions).

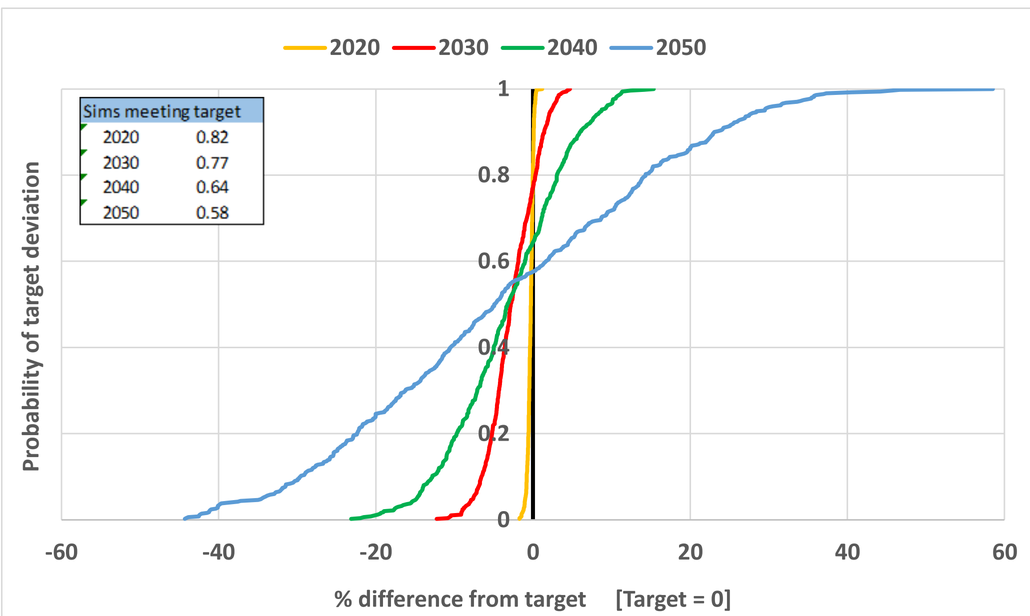


Figure 6 Probability of % deviation from targets across model years under Reference carbon prices

A conclusion from this analysis is that in the long term 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.[8] The probability of meeting targets under the high / low carbon prices in 2030 are shown in Figure 7.

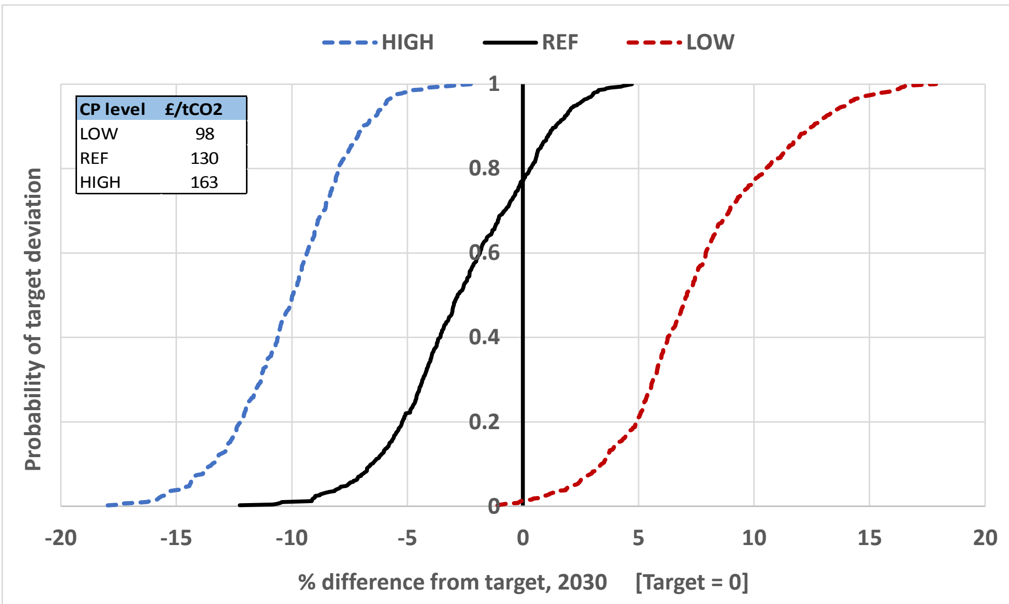
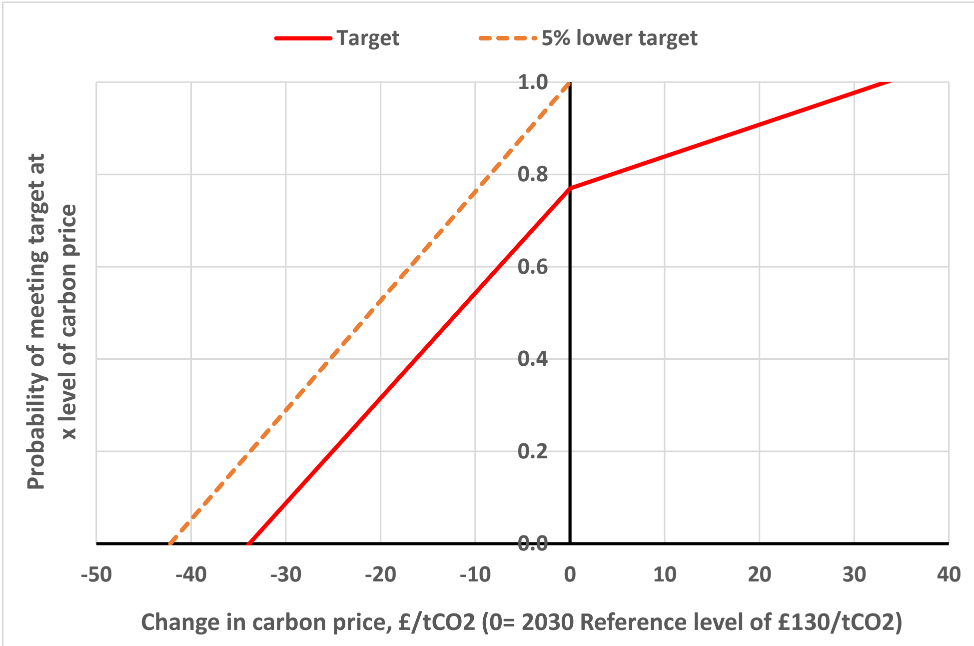


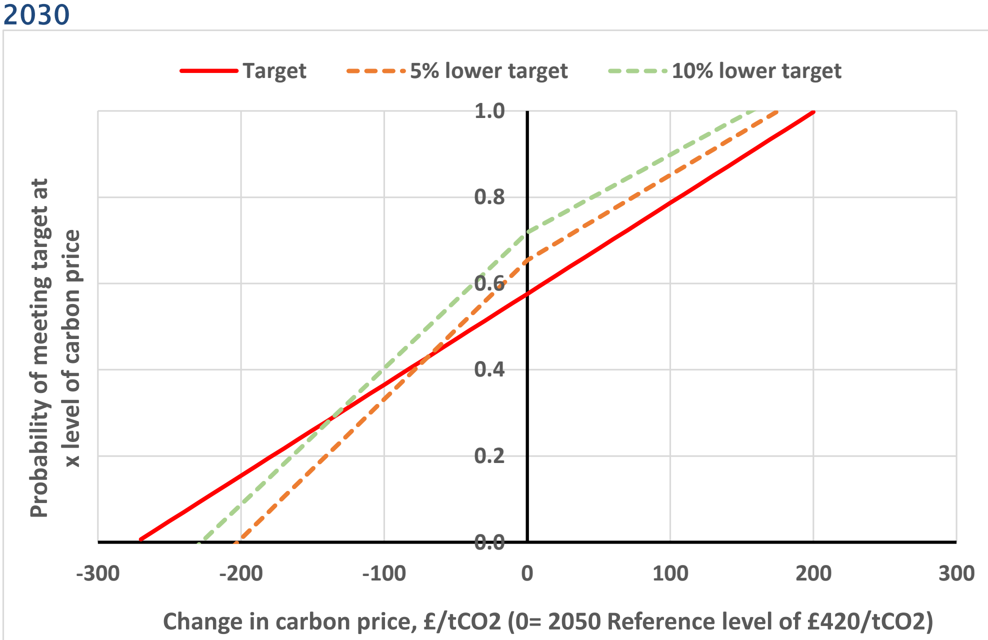
Figure 7 Probability of % deviation from targets in 2030 under different carbon prices (Carbon price levels for each set of simulations are shown in the top left corner of the graph)

The results can be used to estimate an approximated relationship between the carbon price level price and the number of simulations meeting targets in a given year (Figure 8). The analysis shows that the model is highly sensitive to the carbon price level in 2030. Under the Reference price, 77% of simulations meet the target level; however, this drops to zero based on a £35 reduction in price (or 26% reduction). Conversely, a £30 increase leads to 100% of simulations meeting the target. If we consider simulations that are within 5% of the 2030 target, 100% of simulations meet the target under the Reference price. This analysis implies that carbon price level in the mid-term is extremely sensitive, with a sharp decline in the probability of staying on the proposed transition pathway if the carbon price level is not at a sufficient level. Conversely, the level of carbon price increase to strongly mitigate the uncertainty of meeting the target level is modest.

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



2030



2050

Figure 8 Impact of change in carbon price on probability of meeting targets in 2030 and 2050 (<5% or <10% show the probability based on meeting the target within a 5% or 10% margin)

In 2050, the carbon price range in which all or no simulations meet the carbon reduction level is much larger (+£200 /– £270 of the reference price). The analysis also highlights the carbon price level reductions if simulations had to meet a target that allowed for reduction levels that were 5-10% lower (less stringent). Under a 10% margin, the 2050 value for all simulations meeting the target drops to an increase of £150;

however, this is still a very high carbon price of around £570/tCO_2, compared to one of £620 /tCO_2 where there is no assumed margin. 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. This could also be endogenized in the model by running a constraint programming model counterpart where the environmental target is set to be met to a determined percentage.

It is also possible to estimate the downside risks of the simulation solutions (Sabio et al. 2010) by evaluating in relative terms the potential losses associated with the solution obtained through the model runs that meet or do not meet the target. If we name *d* the designs to be considered, where one includes the model solutions that meet the target, and the other one those that do not, it is possible to evaluate the risk associated with the probabilities of having a system cost higher than the average expected system cost across simulations. The downside risk metric used can be expressed as follows:

$$DRisk(d,\Omega) = \sum_{i=0}^{N} p_N \partial_N (d,\Omega) \quad (3)$$

$$\partial(d,\Omega) = \begin{cases} Total\ Cost\ (d) - \Omega & if\ Total\ Cost\ (d) > \Omega \\ 0 & Otherwise \end{cases} \quad (4)$$

Where *d* are the set of energy system designs meeting or not the target and Ω is the total system cost obtained in the deterministic run. The downside risk is a metric that measures the additional costs incurred by being below or above the emissions target. Table 5 presents downside risk for different systems.

Table 5 Downside risk metrics of different systems in 2050

Risk metric	Carbon Price (£/tCO_2)	Design	Value (£)
Downside Risk	Low (£316)	Meet 2050 target	$3.29 \cdot 10^{12}$
Downside Risk	Low (£316)	Not meet 2050 target	$1.22 \cdot 10^{12}$
Downside Risk	Ref (£421)	Meet 2050 target	$4.69 \cdot 10^{11}$
Downside Risk	Ref (£421)	Not meet 2050 target	$8.00 \cdot 10^{11}$
Downside Risk	High (£527)	Meet 2050 target	$3.33 \cdot 10^{09}$
Downside Risk	High (£527)	Not meet 2050 target	$8.20 \cdot 10^{10}$

The results indicate that the downside risk of not meeting the target is much higher than downside risk of meeting the target for high carbon prices, and almost double in the case of the reference carbon prices. Interestingly, the low carbon price level increases the downside risk, in magnitude and in relative terms for the designs that meet the target. This result illustrates how a low carbon price level does not provide sufficient insurance to invest in low carbon technologies; rather the risks of not meeting the target (and incurring payment) are lower. This level of risk provides a good indicator of the economic benefits of meeting the targets by 2050 and suggests the level of costs that can be absorbed by meeting the targets as well as the required carbon prices that would allow objectives to be met.

The remainder of this section explore the underlying system choices that characterise those pathways that meet (or not) the emission reduction levels. We focus on those sectors / technologies for which we have characterised uncertainty, namely power generation, road transport (particularly cars), heating in buildings and the role of biomass.

4.2 Power generation system evolution

The power generation system is key to decarbonisation of the energy system, as much of the cost-effective potential is in this sector. Figure 9 illustrates the large reduction in carbon intensity of generation across all simulations, down from 2010 levels of over 480 gCO_2/kWh. While the reference carbon price drives carbon intensity levels down across all simulations, a clear distinction emerges in intensity between those meeting the target or not. In 2030, 70% of runs meeting the target (MT) are at a lower carbon intensity than all simulations that do not the target (NMT). This implies an important role for power sector decarbonisation in meeting mid-term targets, and supports the CCC guidance that a low carbon intensity of generation is required by 2030 (CCC 2013).

In 2050, the reference carbon price ensures a decarbonised generation system. The carbon intensity of generation is on average -46 gCO_2/KWh for simulations that meet the target, compared to -30 gCO_2/KWh for those that do not. This implies a stronger role for biomass-based CCS technologies to meet the 2050 target, which provide negative emission credits, by capturing and storing emissions from biomass deemed to be carbon neutral.[9] Interestingly, biomass-based CCS technologies are deployed in 70% of all simulations (irrespective of targets being met or not), highlighting the important role this technology has under the longer term target. It also emphasises a critical uncertainty not included in this analysis; there may be circumstances in the future where such a technology may not be available, or the use of negative emission options ruled out on policy grounds. These 'in-out' possibilities are not considered; uncertainty is only attributed to the technology cost and the rate of annual build. This potentially narrow view of uncertainty is reflected across all uncertainty distributions, and highlights the need for additional research on the uncertainty space not covered.

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

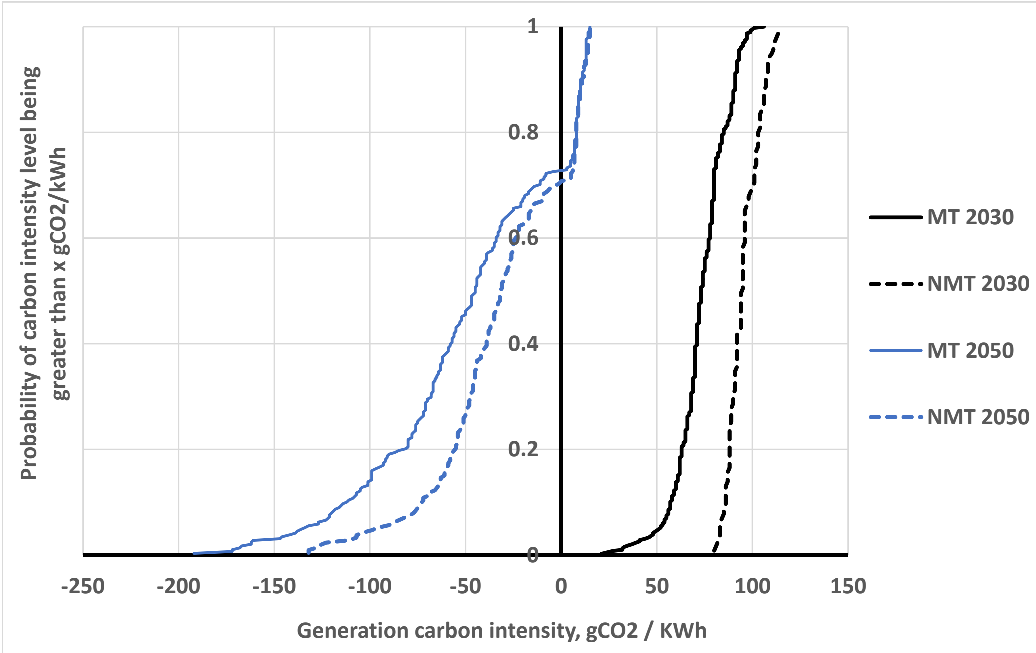


Figure 9 Cumulative probability of carbon intensity of electricity in 2030 and 2050 in Sims meeting / not meeting target (MT / NMT)

The reference carbon prices push the energy system towards a high levels of electrification in all simulations, reflected by similar levels of total generation. Uncertainties across technologies do not undermine this pattern, with low standard deviation from the mean observed. The distribution of generation levels by technology in 2030 are shown in Figure 10. The main difference between the two sets of simulations appears to be between CCGT and nuclear, with nuclear generation much higher on average in runs that meet the target, and much lower for CCGT. The probability for generation from CCGT with CCS is broadly consistent between the two time series, and higher than other generation types, indicating the importance of this technology under carbon prices irrespective of uncertainties.

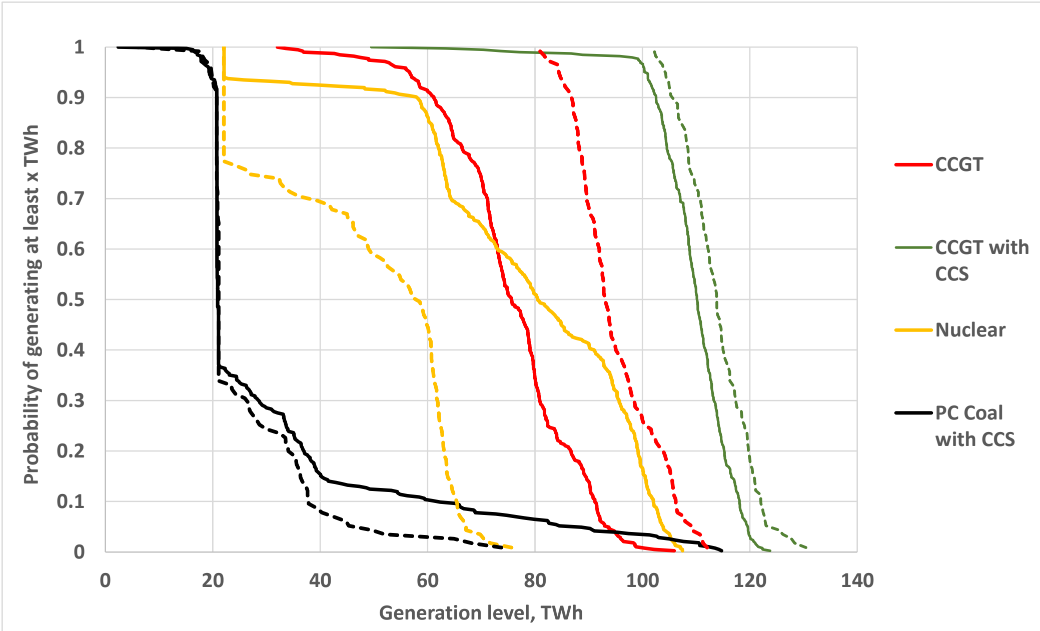


Figure 10 Probability of electricity generation levels being at least at a specific level in 2030 in Sims meeting / not meeting target (dashed time series denote runs not meeting target)

In 2050, the level of 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 Figure 7 are 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 (36 TWh of biomass IGCC w/CCS in the 70% of simulations meeting the target, out of a total average generation of 532 TWh).

The dominant role of either nuclear or gas CCGT w/ CCS is shown in Figure 11 for those simulations meeting the target, with important contributions observed from wind and IGCC biomass w/ CCS. While it is evident that the electricity generation sector will be decarbonised by 2050, the choice of technology could differ significantly depending on costs. While all simulations have both CCS and nuclear as generation types, the model choice appears particularly sensitive to the capital cost of nuclear in determining its contribution (up to a maximum 313 TWh, or 40 GW of installed capacity), while for CCGT w/ CCS, it is the gas price. Uncertainty around gas prices and nuclear costs appear to be key determinants of technology investment decisions in the power sector, and lead to some very distinctive pathways. This emerges strongly in the sensitivity analysis in section 4.6.

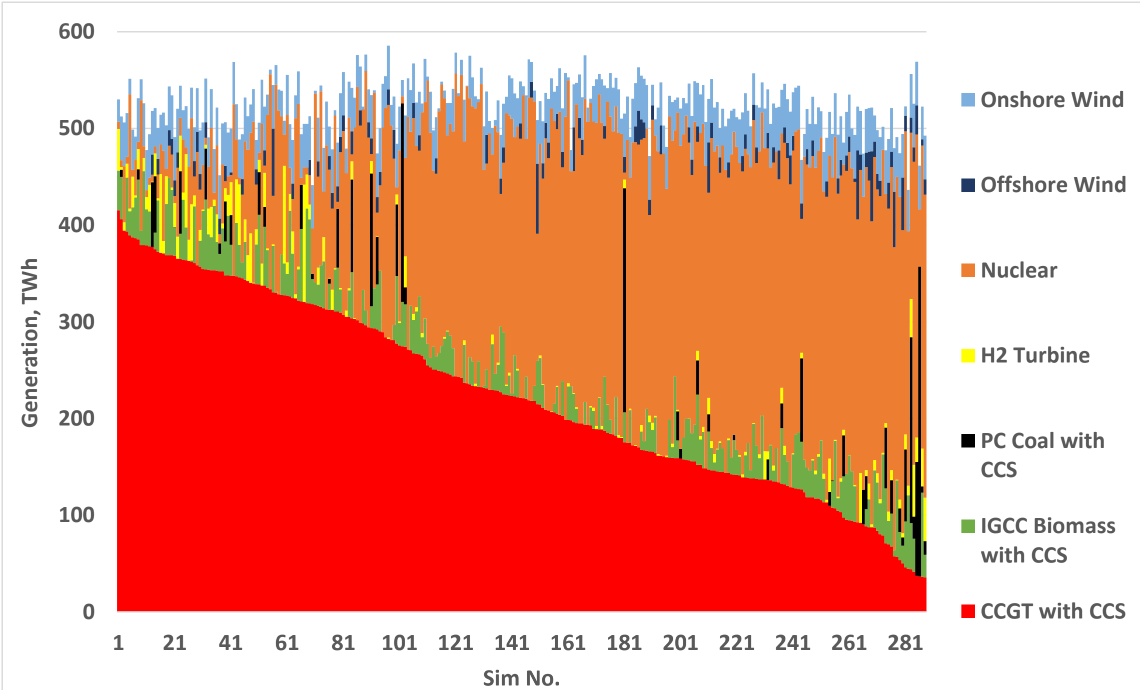


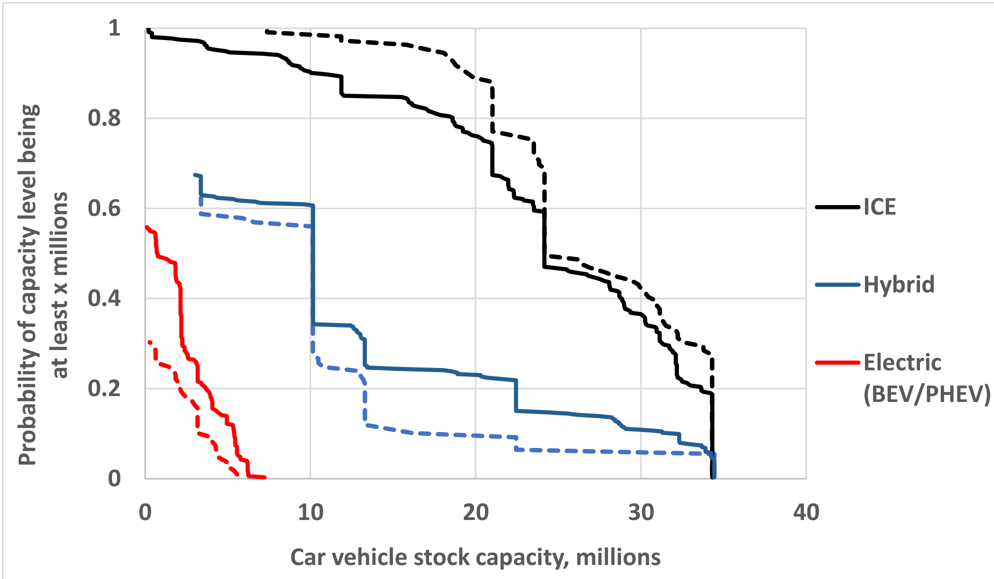
Figure 11 Electricity generation level in 2050 by technology type in Sims meeting targets

The choice of gas for generation in the long term has important supply side implications. At the average 250 TWh of generation from CCGT w/CCS in 2050, this would mean higher sectoral use than in 2010. The overall consumption of the system would be lower due to reductions in other sectors, notably buildings. However, the power generation sector would maintain levels at around 70% of 2010 system consumption. Supply at this level could increase exposure to import disruption, and also highlights the potential role for continued domestic production, including shale gas.

4.3 Transport car technology uptake

Meeting long term targets in 2050 requires strong decarbonisation efforts in the transport sector. Cars, which account for 55% of sector emissions in 2010, are the focus here. The uptake of car vehicle technologies in 2030 is shown in Figure 12, and highlights the higher uptake of hybrids than ICE vehicles in simulations that meet targets. The uptake of electric vehicles (BEVs / PHEVs) is also higher, albeit at much lower rates than indicated in the CCC pathway. A higher share of liquid fuel use in the car stock can be maintained due to the higher share of mitigation in other sectors, use of biofuels (on average, 9% of fuel use – and in part, produced using CCS technology) and assumed efficiency gains across hybrid / ICE vehicles. Another reason for lower penetration of electric vehicles could be a limitation in the modelling, where the flexibility concerning timing of charging (to use the lowest price electricity) is limited.

2030



2050

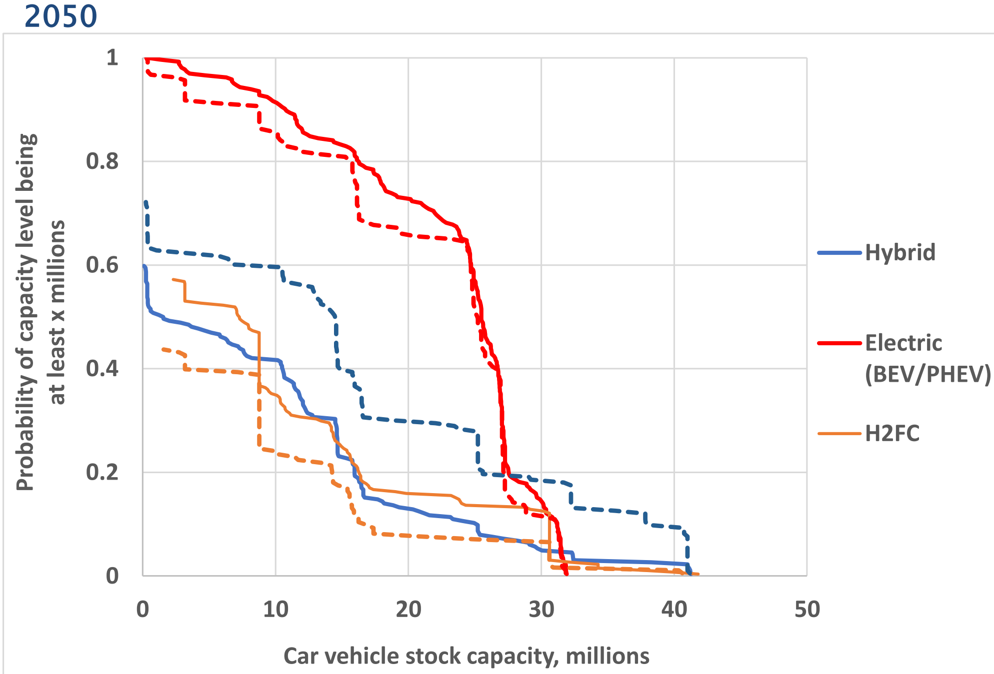


Figure 12 Probability of car stock level by type being at least at a specific level in 2030 and 2050 in Sims meeting / not meeting target (dashed time series denote runs not meeting target)

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). Power sector decarbonisation drives this higher contribution compared to hydrogen vehicles. The main differences between the two sets of simulations include a stronger role for hydrogen and reduced role for hybrids in the simulations that meet the target. An important factor is at play in the road transport sector – the role of biofuels. The share has doubled in the model relative to 2030 levels, allowing for continuing use of hybrids and to a lesser extent ICEs (not shown in the above graphic). Domestic production of biofuels is favoured due to biofuel production with CCS, allowing for negative emissions (as described in section 4.5). Without such technologies, it is likely that the role of hydrogen and electric vehicles would be even greater in the car stock by 2050, compared to their current contribution (Figure 13).

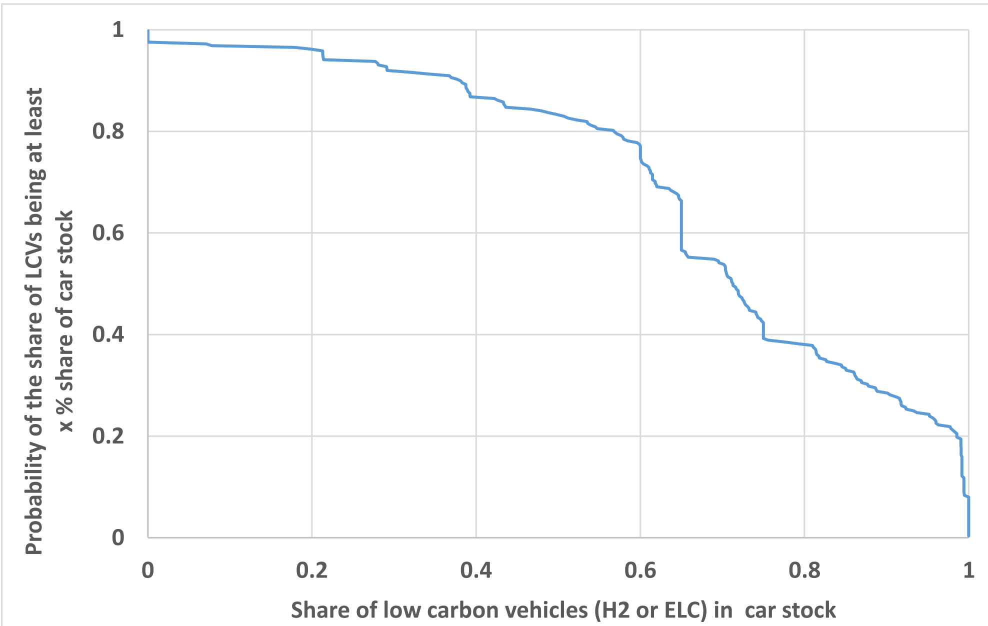


Figure 13 Probability of share of low carbon vehicles (H2 or ELC) in car stock being at least x % in 2050 in Sims meeting target

4.4 Heating provision in buildings

Heating provision, which accounts for the largest share of energy demand in the building sector, does not differ significantly in either period of interest, between simulations that meet or do not meet the target. The reference CO_2 prices deliver similar levels of heat pumps and district heating in both 2030 and 2050 across simulations. The average space heating production by technology is shown in Figure 14, and reflects the system observed in the Reference deterministic run. Standard deviation for any technology type is low, in the range of 5-15.

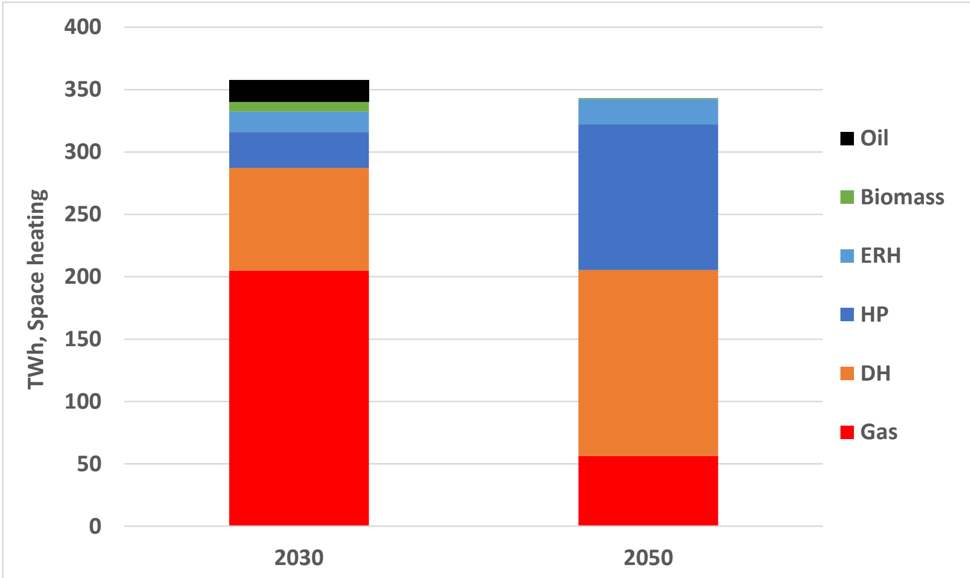


Figure 14 Space heating production (average) by technology type (ERH = electric resistive heating, HP = heat pumps, DH = district heating)

Only a limited set of uncertainties were considered in this sector, and therefore the model outputs should not be surprising. Further uncertainties should be explored, with a focus on infrastructure build and demand side measures rather than the technology cost. For example, district heating in 2030 is largely delivered via recoverable heat from large power plants (due to low production costs). The uncertainties around the feasibility of this system orientation require further consideration, particularly as network heat infrastructure investment from larger plant could be considerably higher than from decentralised district heating plant. Additional uncertainty arises from the other main district heat production technologies – large scale marine heat pumps and geothermal plant, both of which are relatively immature technologies (at least in the UK), and therefore highly uncertain.

4.5 Energy system biomass use

Biomass resource availability appears to play an important role in meeting long term carbon reduction targets, and this emerges strongly in the sensitivity analysis in section 4.6. The simulations highlight the large difference between biomass use in those meeting the target versus runs where they do not (Figure 15). Where the reduction target is met in 2050, average biomass use is 349 TWh (s.d. 58) compared to 195 TWh (s.d. 40). The apparent impact of biomass resource availability uncertainty is linked to its use in CCS technologies for power production and biofuel production. This also highlights that the model is predisposed towards the use of biomass in CCS as a critical mitigation option in the longer term, and that uncertainties relating to the use of biomass in this way should be considered in greater detail. For example, uncertainties relating to biofuel production (including those using CCS) were not included in this analysis i.e. were held deterministic.

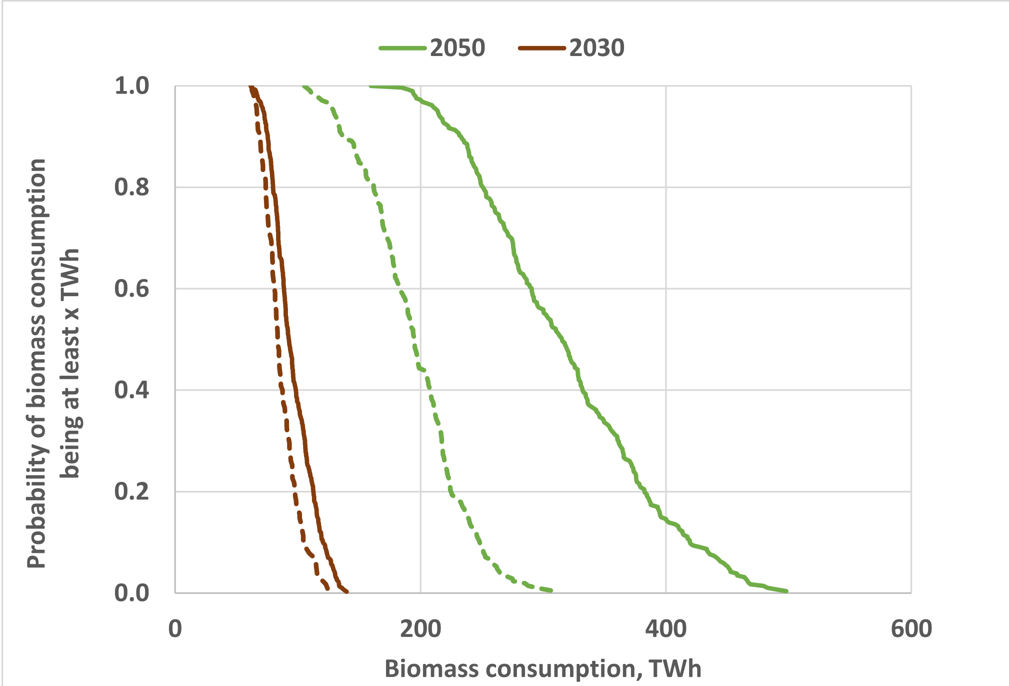


Figure 15 Probability of biomass consumption being at least x TWh in 2030 and 2050 reflecting uncertainty on resource availability (dashed time series denote runs not meeting target)

The biomass availability range is based on the three scenarios considered in the CCC Bioenergy Review (2011b), with biomass availability (domestic and imported) between 100 and 500 TWh, with 200 TWh as a central value (or mode in the triangular distribution). The key issue is how this biomass could be used, and to what extent it would be used in biomass-based CCS, for power generation or domestic biofuel production. This is a key question, and one that should be subject to further uncertainty analysis given the model's predisposition to choosing such fuel-technology combinations.

4.6 Sensitivity analysis

In this section, we present the results of the sensitivity analysis, described in section 3.5. The purpose of this analysis is to explore the sensitivity of the model output to the input uncertainties. The sensitivity analysis is performed on two key outputs in 2050, total system costs and total CO_2 emissions. Figure 16 presents the probability density functions obtained for the outputs of interest. The results can be taken as statistically representative and coherent with the expected results after performing the calculation of the number of samples in Section 3.4. The estimation of the mean with the Monte Carlo simulations has less than a 1% error, as predicted by the calculation of the number of samples required (described in Section 3.5).

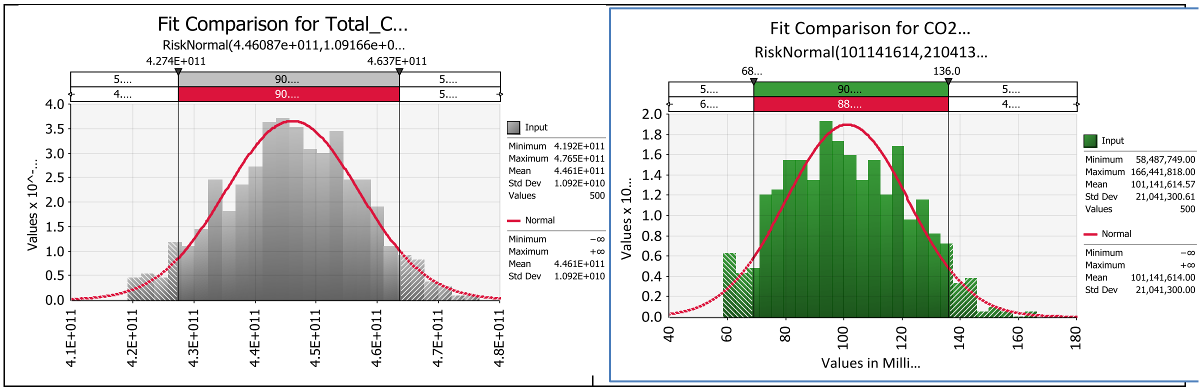


Figure 16 Frequency histogram and normal distribution fit for output metrics total system costs and total emissions (in 2050)

The first step of the sensitivity analysis is to simply observe the scatterplots for correlations (in Appendix 2). This provides an understanding of how correlated input uncertainties are with the above output metrics. For total system costs, the obvious correlations include, from left to right, nuclear capital costs, gas price and biomass resource availability (see Figure 17).

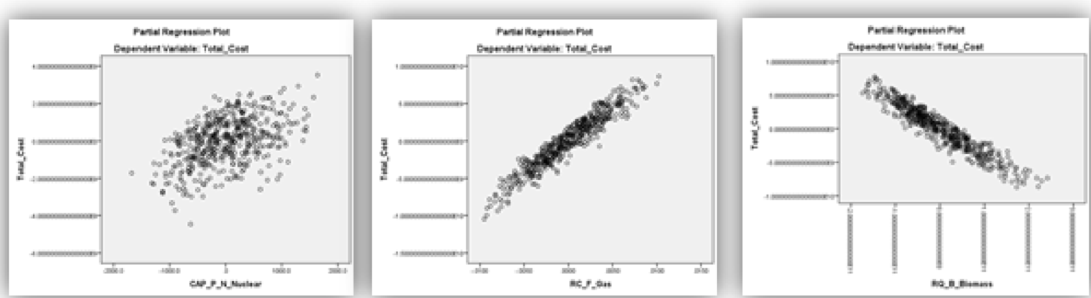


Figure 17 Scatterplots of nuclear power plant costs, gas prices and biomass resource availability versus total system costs.

This suggests that all three factors independently have an important impact on total system costs. For total CO_2 emissions, biomass resource availability (Figure 33) provides the only obvious pattern (lower emissions at higher availability). Our observations in the previous section also highlight the importance of these uncertainties. Shaped patterns are also observed for diesel fuel, and other resources and transport vehicles capital costs; however, no immediate conclusions can be drawn from these observations.

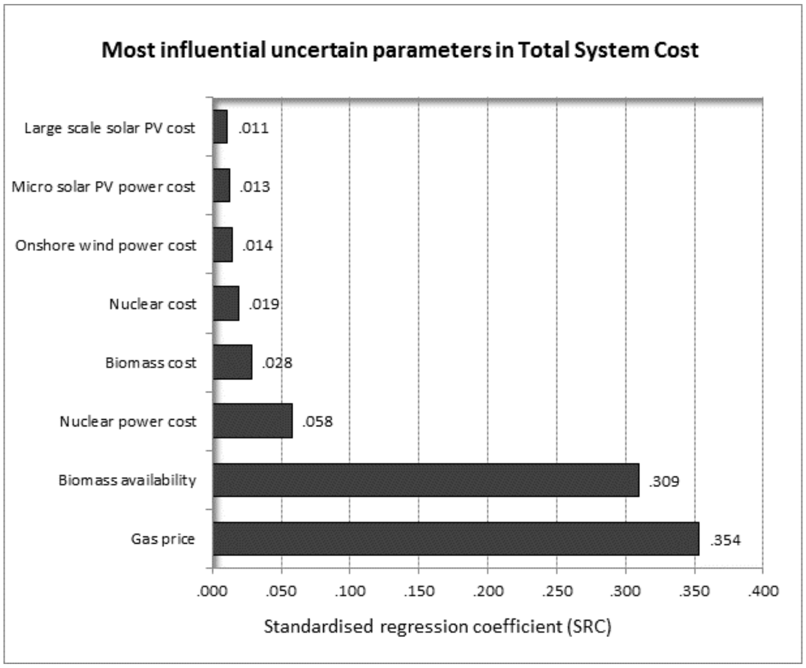
While these scatterplots provide some useful first indications of key uncertainties, they do not provide further insights for the less obviously correlated metrics and insights into how their combined uncertainties impact on the output metric variability. To further investigate model sensitivity, we perform a multivariate linear regression. Using the estimated standardised regression coefficients as our first order sensitivity indices, we can 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 Equation 3) obtained for the two output metrics of interest as presented in Table 6.

Table 6 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

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 the corresponding linear regression models fit 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 standardised regression coefficients (SRC). 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 and least influential parameters for the total system costs and emissions are presented in Figure 18 and Figure 19.



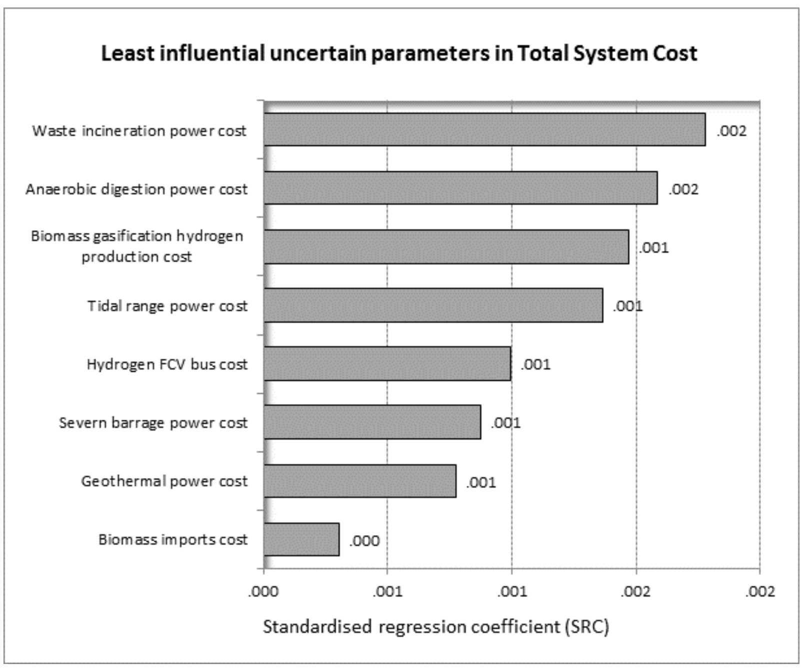


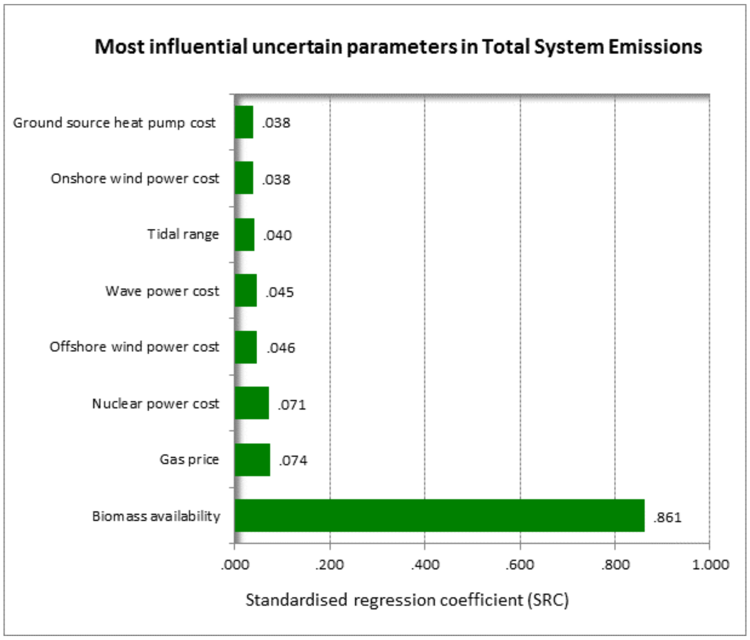
Figure 18. Standard regression coefficients (SRC) parameter rank from multivariate regression analysis – total system costs

Figure 18 shows the factor prioritisation (key uncertainties impacting most strongly on total system cost solution) and fixing metrics (key uncertainties impacting least on total cost solution) from the multivariate regression analysis. The most important parameters show those revealed in the scatterplots as the most important uncertainties affecting the total system costs. Reduced availability of biomass has significant implications for costs, with increased costs due to payment of carbon price under simulations where less biomass is available. The continued importance of gas in power generation, in CCS technologies, means a strong impact on system costs when resource cost increases, and highlights potential security of supply risks. Additionally domestic biomass resource costs and nuclear resource costs are revealed as influential factors, along with onshore wind, solar PV and tidal stream power generation costs. Interestingly the build rates and transport vehicles costs do not appear as highly influential factors.

On the other hand, the factor fixing exercise reveals that although biomass resource availability and costs have a high influence in the model, the biomass imports costs variability is not having a high impact in the total system costs. This is likely to be due to the fact that imported biomass cost uncertainty does not matter in later periods (when imports are most required, above indigenous resource), as the model wants to utilise biomass as much as possible; hence, the importance of availability as opposed to resource cost. Geothermal, Severn Barrage, tidal range and recovered bioenergy based power technologies do not appear to be important sources of uncertainty. The same is true for hydrogen FCV bus costs and hydrogen production costs from biomass gasification technologies.

Figure 19 shows the most and least influential parameters in relation to total system emissions. As expected, (and seen in the scatterplot analysis) biomass availability is by far the most influential uncertain parameter, followed by nuclear power costs and gas prices. Up to this point the results are in line with the most influential parameters observed when analysing the total system costs. Offshore wind, wave and tidal range power costs appear as the next set of most parameters whose variability affect the system emissions the most. A non-intuitive insight that can be obtained from this analysis is the trade-off that some of the model parameters present in terms of costs and emissions. An example of this is the tidal range power costs, which appear as a non-influential parameter in terms of system costs, but a highly influential parameter in terms of emissions. Also onshore power cost appear influential in terms of emissions and in line with the results obtained for the system costs, while ground source heat pumps cost is revealed as a new influential parameter in the system emissions.

Least influential parameters include waste incineration and hydrogen FCV bus costs, also observed for systems costs. Nevertheless in the case of emissions micro solar power technology costs appear not to be an influential parameter in terms of emissions, whereas more influential for the total system costs. Geothermal, biomass fired and macro CHP technologies cost appear as non-influential parameters in the systems emissions, as could be expected, along with electrolysis and coal gasification with CCS hydrogen production technology costs.



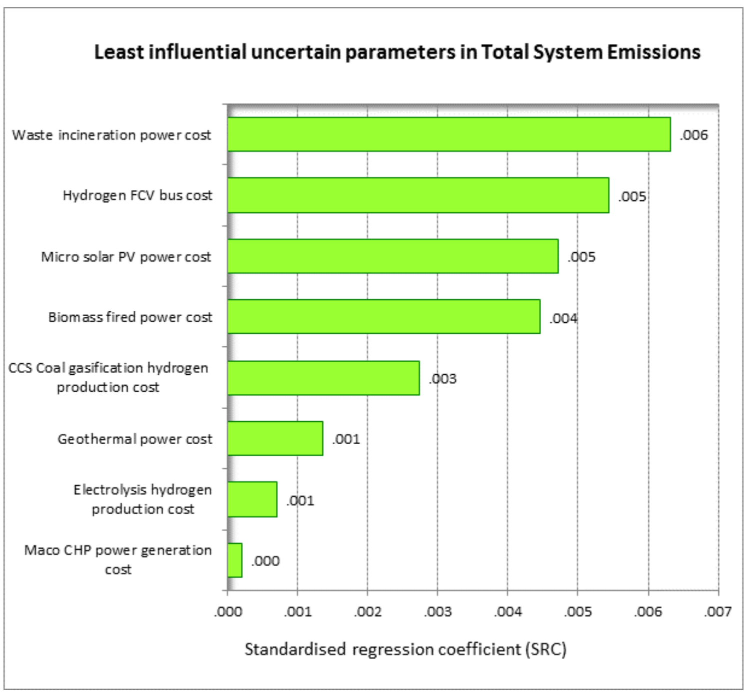


Figure 19. Standard regression coefficients from multivariate regression analysis – total system emissions

These results provide important understanding about the relative importance of input uncertainties on the total system costs (objective function) and emissions. This is critical for understanding of the model sensitivity, and provides a useful for basis for further development of uncertainty analysis in ESME. For those uncertainties that are most influential, these should be subject to greater scrutiny, while other less influential uncertainties could be dropped from the analysis.

5 Conclusion and policy implications

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/tCO_2) results in a very 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 incentives 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. It is clear that a key uncertainty driving model choice in 2050 is the availability of biomass, ranked as very influential for both costs and emission metrics in the sensitivity analysis. The option to use biomass in CCS plant (either for power generation or biofuel production) is extremely attractive under high carbon price levels; therefore under simulations where biomass availability is high, there is a stronger likelihood of the target being met. Additionally, further consideration needs to be given to the level of biofuels in the longer term that might be appropriate, and uncertainty around the costs and build rates of biofuel production plant with CCS. Radically different policy positions on the use of biomass in CCS should be another uncertainty considered.

In 2050, the relative shares of low carbon generation technologies are sensitive to capital costs for nuclear, and gas prices for CCGT w/ CCS, as shown by the sensitivity analysis. Deployment of either technology does not differ under simulations where targets are met or not met, highlighting that by 2050, all generation technologies have a low or zero carbon intensity. In the transport sector, there appears to be a trade-off between penetration of hydrogen in simulations where the target is met, and much lower uptake of hybrid vehicles. The level of electric vehicle does not differ significantly, reflecting the high level of system electrification under all simulations (and therefore the attractiveness of this technology). The persistence of ICE and hybrid electric vehicles links to the increase in domestic biofuel production (biomass with CCS) described above.

In coming to the above conclusions, we need to be cognisant of how model set-up impacts on our results. Uncertainties arise from the model structure and how we propagate the probability distributions. In 2030, it evident that uncertainty is much lower than in 2050, due to the approach of indexing of 2050 sampled values back to 2010. This indexing approach implies near term uncertainties are lower than in the longer term, and leads to a conservative range. In addition to reconsidering the level of uncertainty, it is worth noting the uncertainties we have focused on. There is already some bias towards the power generation sector and transport sectors, which account for 75% of all uncertain inputs. It may therefore be unsurprising that limited impacts are observed from uncertainties across building sector assumptions.

Additional uncertainties could also be considered. Of particular interest, is the role of CCS in 2030, with an average 15 GW of CCGT w/CCS and some limited biofuel production with CCS. It would be instructive to introduce uncertainty ranges that capture futures where CCS is not viable, and biomass is not used to gain negative emission credits. Other key uncertainties missing include varying rates of uptake of different end use sector transport and heating technologies. It would also be important to consider the broader range of uncertainties in the building sector, observed to be relatively resilient to the impacts of currently modelled uncertainties.

As discussed above, further iteration is required, and this would be most appropriately done in consultation with experts and stakeholders. This would enable better understanding of the extent to which we are observing uncertainties arising as a consequence of the model set-up vs. key uncertainties both affected by and affecting policy development. Furthermore, iteration would also be useful, again informed by the results, as to the uncertainties that may be of less relevance and ones that should be considered in future. It is evident that the role of biomass requires greater scrutiny while other uncertainties may be of less importance. A broader view of uncertainties – including demand side uncertainty, technology failure and financing, public acceptability and ecosystem / material constraints – could also be considered, going beyond the uncertainty space considered in this analysis, which focused on technology trade-offs based on cost-effectiveness. This policy-modelling iteration phase is clearly a critical part of increasing the relevance of such studies for policy making.

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Appendix 1. Overview of model input assumptions

This appendix provides an overview of some of the key input assumptions. Note that all cost data are expressed on a 2010 year basis.

Power sector

Power sector CAPEX assumptions are based on DECC (2013) estimates in the main, with DECC and other international learning rates applied. High – low estimates are initially based on DECC (2013) range values, for date of build (2020 / 2025);[10] out to 2050, these uncertainties are assumed to grow by different rates, as highlighted in Table 7.

Table 7 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

[10] 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.

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%.*

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 8 below.

Table 8 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

Build rates assumptions used in the model for key selected technologies are shown in Table 9.

Table 9 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

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 Table 10 and Table 11.

Table 10 Transport sector Car CAPEX assumptions, £/vehicles

Technology	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 11 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
		Elc.	0.07	0.06	0.05	0.05	0.05
Car PHEV	Med Range A/B Seg	Liq. Fuel	0.21	0.15	0.13	0.11	0.10
		Elc.	0.10	0.09	0.08	0.07	0.07
Car PHEV	Long Range A/B Seg	Liq. Fuel	0.10	0.08	0.06	0.06	0.05
		Elc.	0.14	0.11	0.10	0.10	0.09
Car Battery	A/B Segment	Elc.	0.17	0.14	0.13	0.12	0.12
Car Hydrogen FCV	A/B Segment	H2	0.24	0.21	0.19	0.17	0.16
Car ICE	C/D Segment	Liq. Fuel	0.64	0.52	0.43	0.38	0.35
Car CNG	C/D Segment	Gas	0.79	0.64	0.53	0.47	0.43
Car Hybrid	C/D Segment	Liq. Fuel	0.49	0.43	0.37	0.34	0.31
Car PHEV	Short Range C/D Seg	Liq. Fuel	0.36	0.27	0.23	0.20	0.18
		Elc.	0.07	0.07	0.06	0.06	0.06
Car PHEV	Med Range C/D Seg	Liq. Fuel	0.24	0.18	0.15	0.13	0.12
		Elc.	0.11	0.11	0.10	0.09	0.09
Car PHEV	Long Range C/D Seg	Liq. Fuel	0.12	0.09	0.08	0.07	0.06
		Elc.	0.15	0.14	0.13	0.12	0.12
Car Battery	C/D Segment	Elc.	0.19	0.18	0.16	0.15	0.14
Car Hydrogen FCV	C/D Segment	H2	0.30	0.26	0.23	0.22	0.20

** Activity per vehicle is 13533 km/yr. 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.*

Resource prices and availability

Fossil fuel resource prices, shown in Table 12, are based on those used in the annual DECC UEP publication (DECC 2013). 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.

Table 12 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.*

The biomass availability range is based on the three scenarios considered in the CCC Bioenergy Review (2011b), 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 13, and are from a paper by Pye et al. (2014). Only the central estimates have been used, with demand response assumptions being held deterministic.

Table 13 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

Appendix 2. Scatterplot analysis

This appendix provides the scatterplots used as part of the sensitivity analysis.

Figure 20. Scatterplots for power sector capital costs versus total system costs, £

Figure 21. Scatterplots for power sector capital costs versus total system costs, £ (Continued)

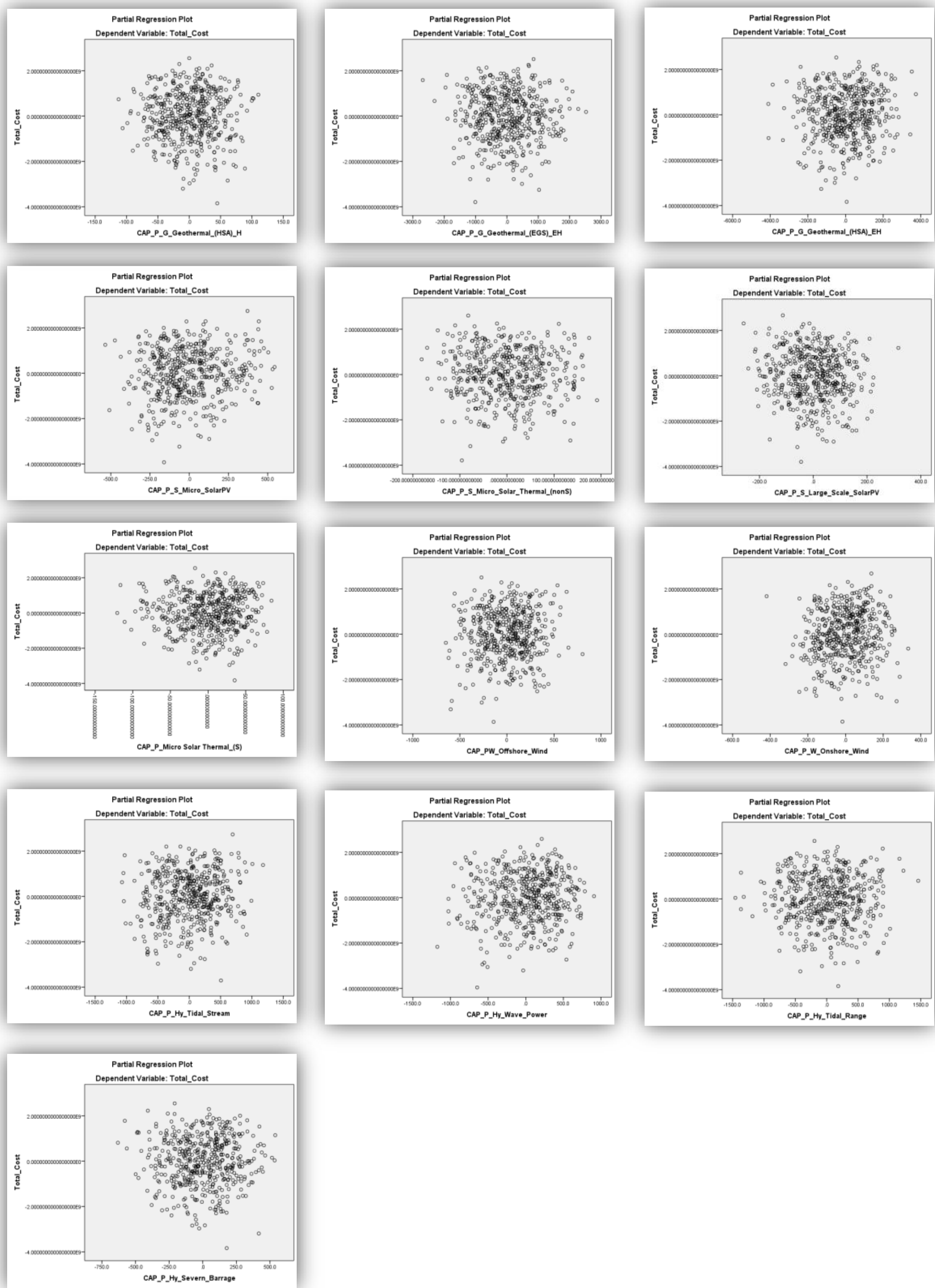
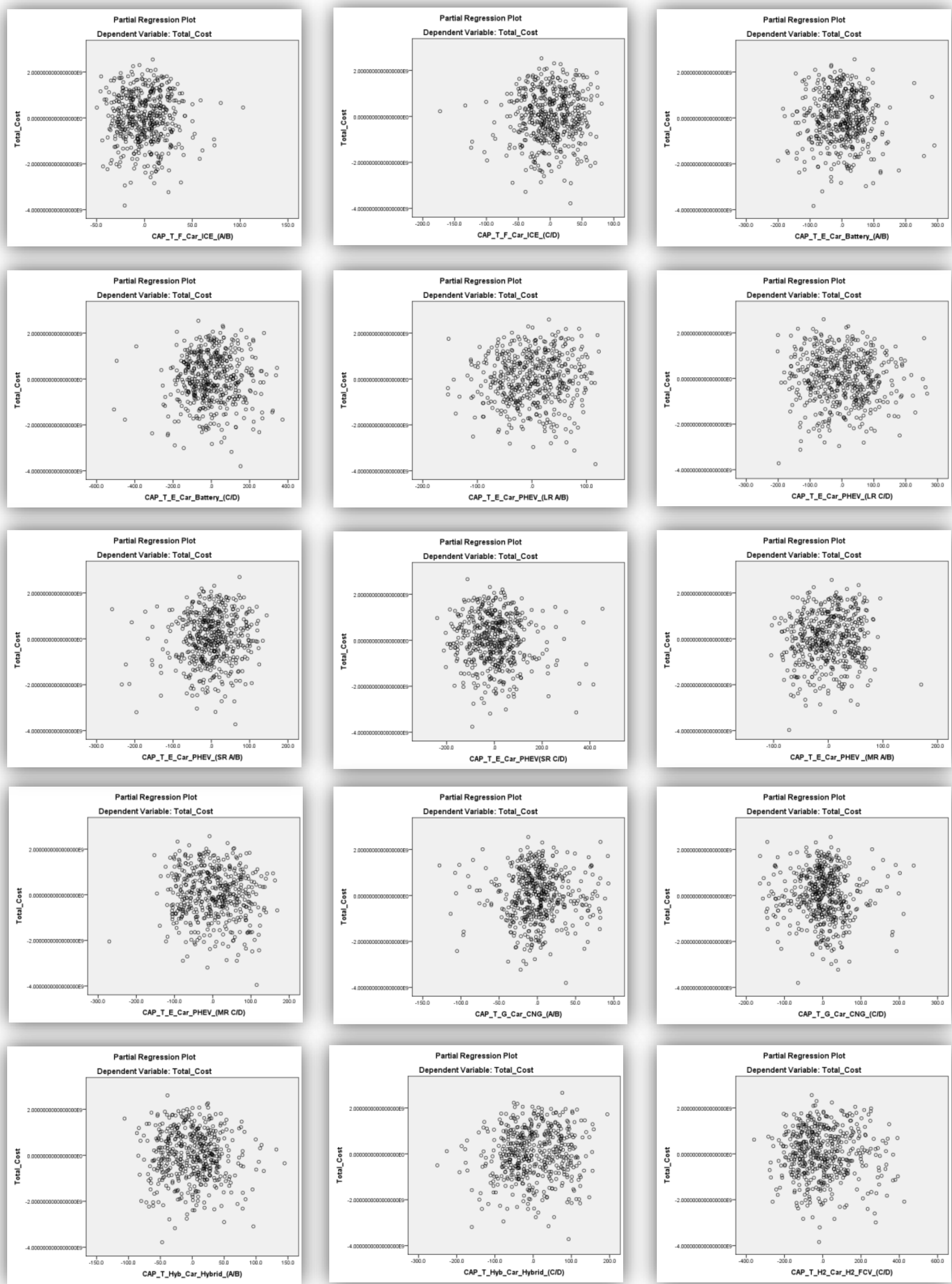


Figure 22. Scatterplots for transport sector capital costs versus total system costs, £



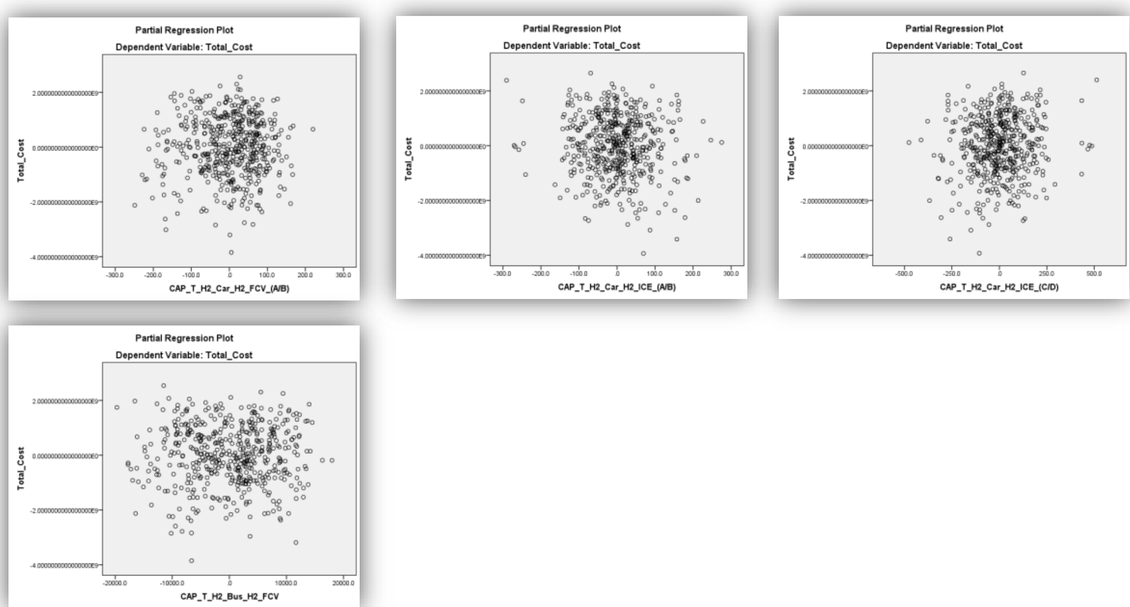


Figure 23. Scatterplots for buildings sector capital costs versus total system costs, £

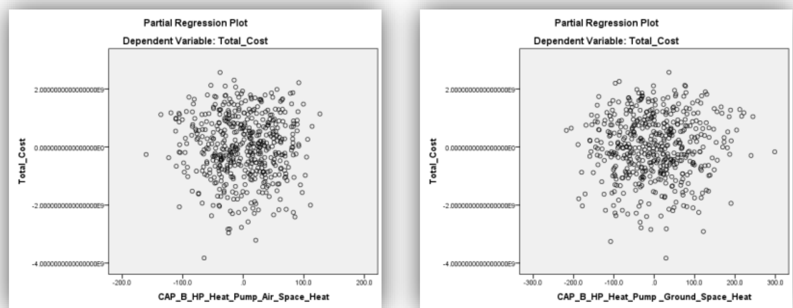


Figure 24. Scatterplot for technology maximum build rates versus total system costs, £

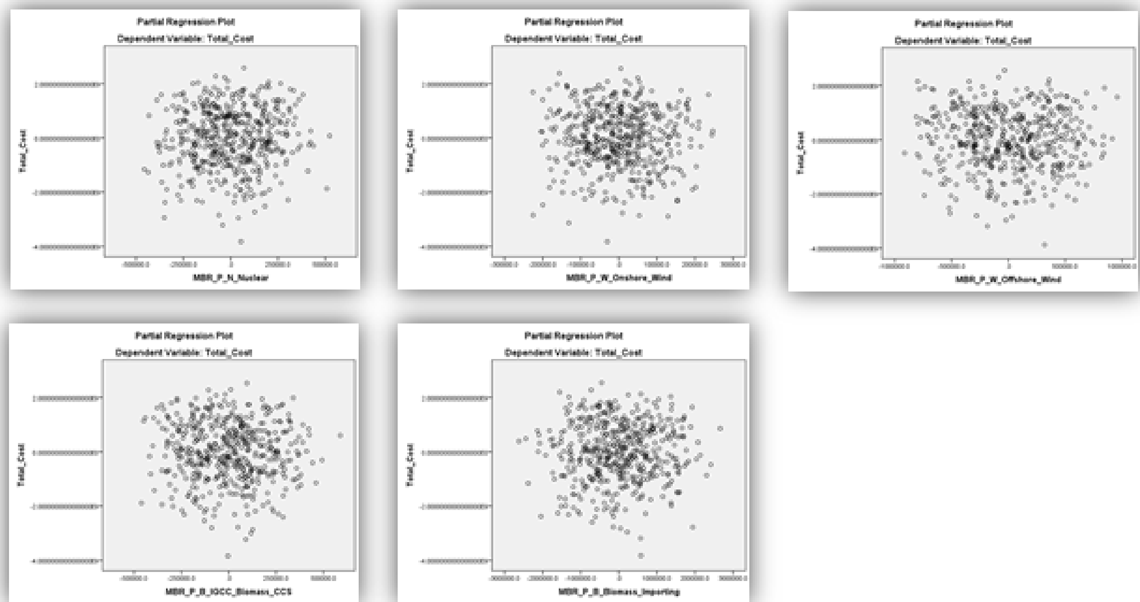


Figure 25. Scatterplot for biomass resources availability versus total system costs, £

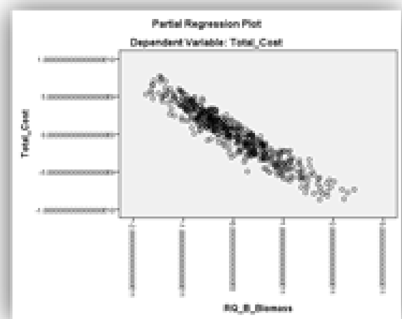


Figure 26. Scatterplots for resources costs versus total system costs, £

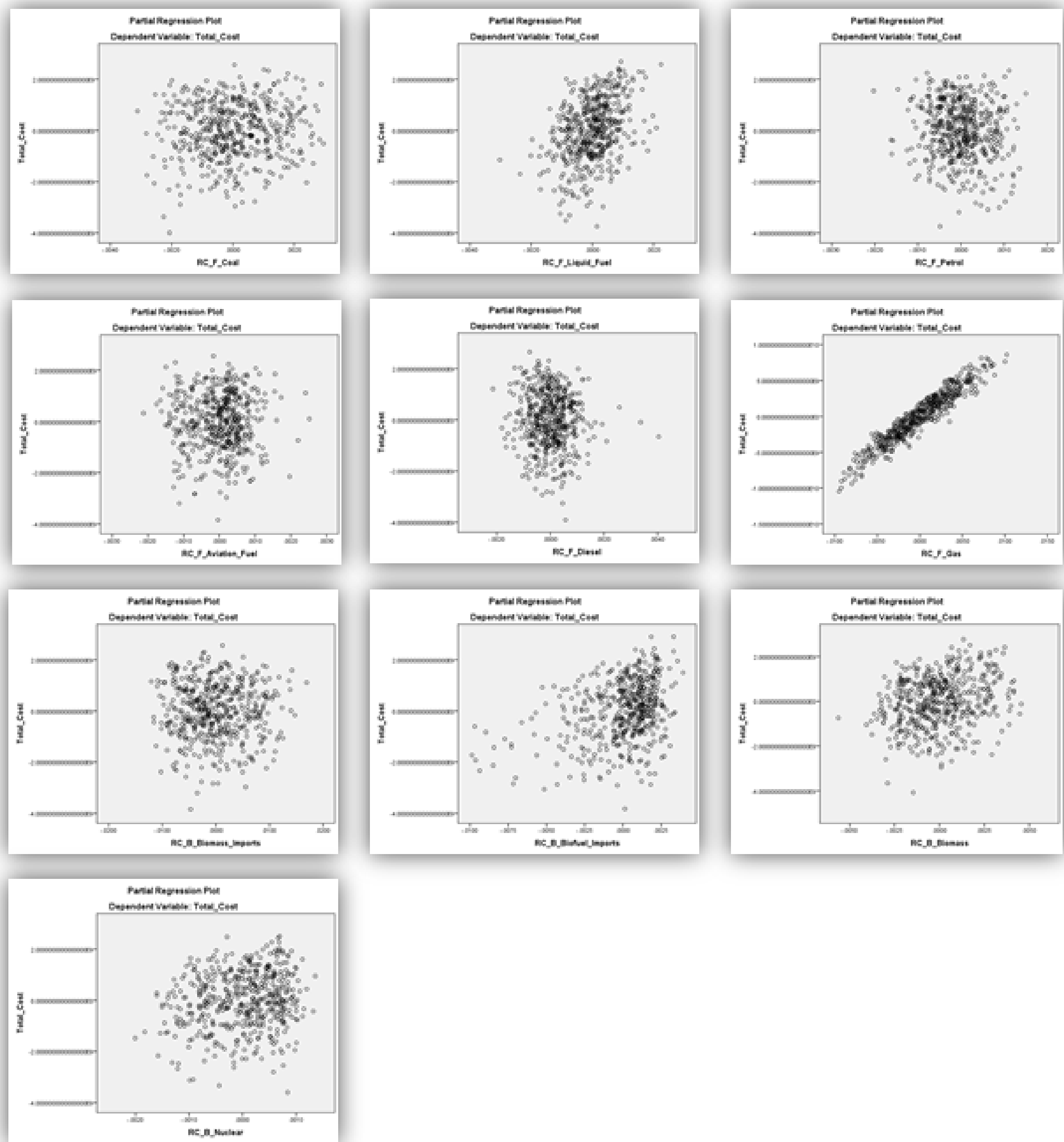


Figure 27. Scatterplots for power sector capital costs versus total system emissions, tCO_2

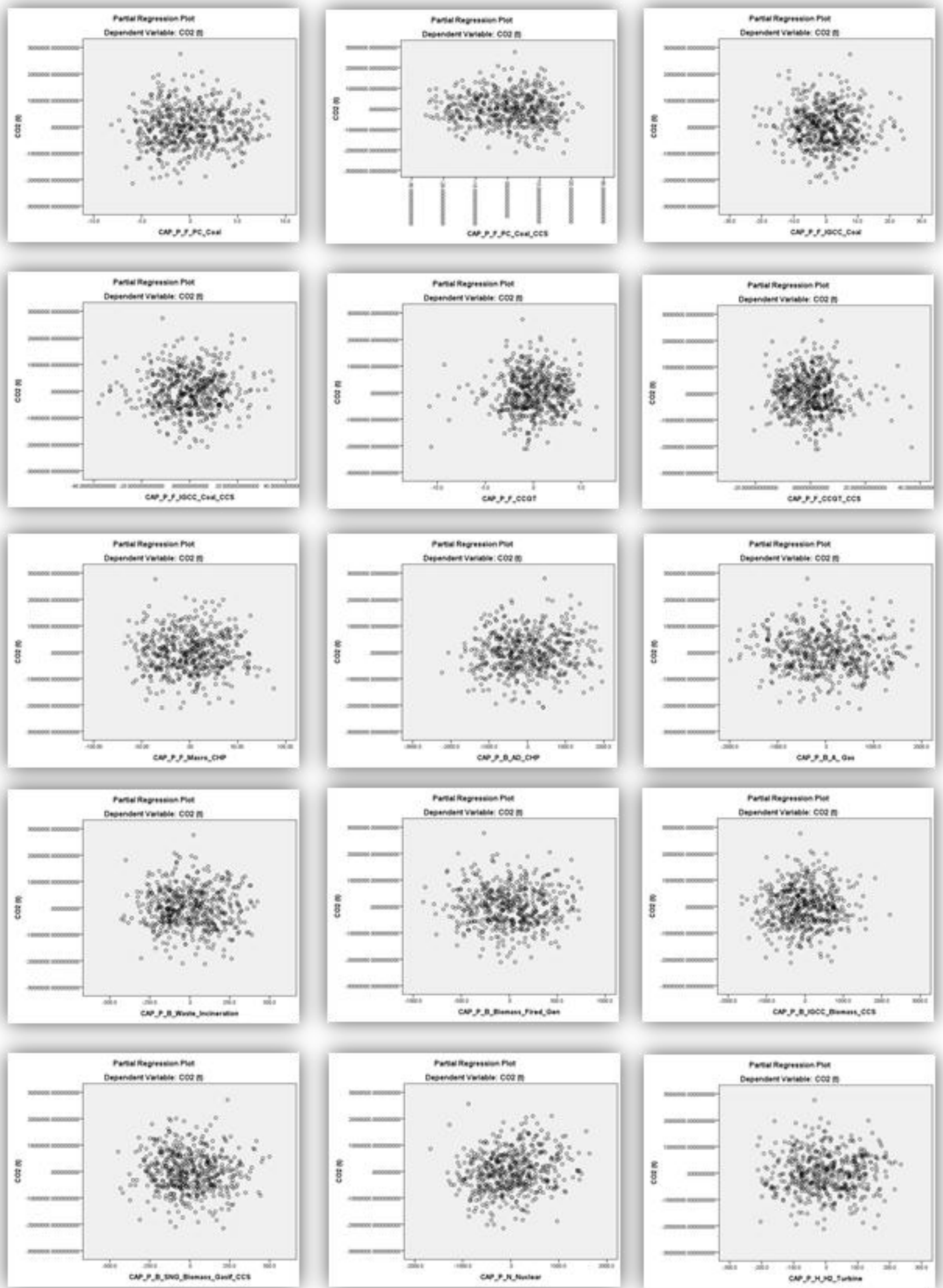


Figure 28. Scatterplots for power sector capital costs versus total system emissions, tCO_2 (Continued)

Figure 29. Scatterplots for transport sector capital costs versus total system emissions, tCO_2

Figure 30. Scatterplots for transport sector capital costs versus total system emissions, tCO_2 (Continued)

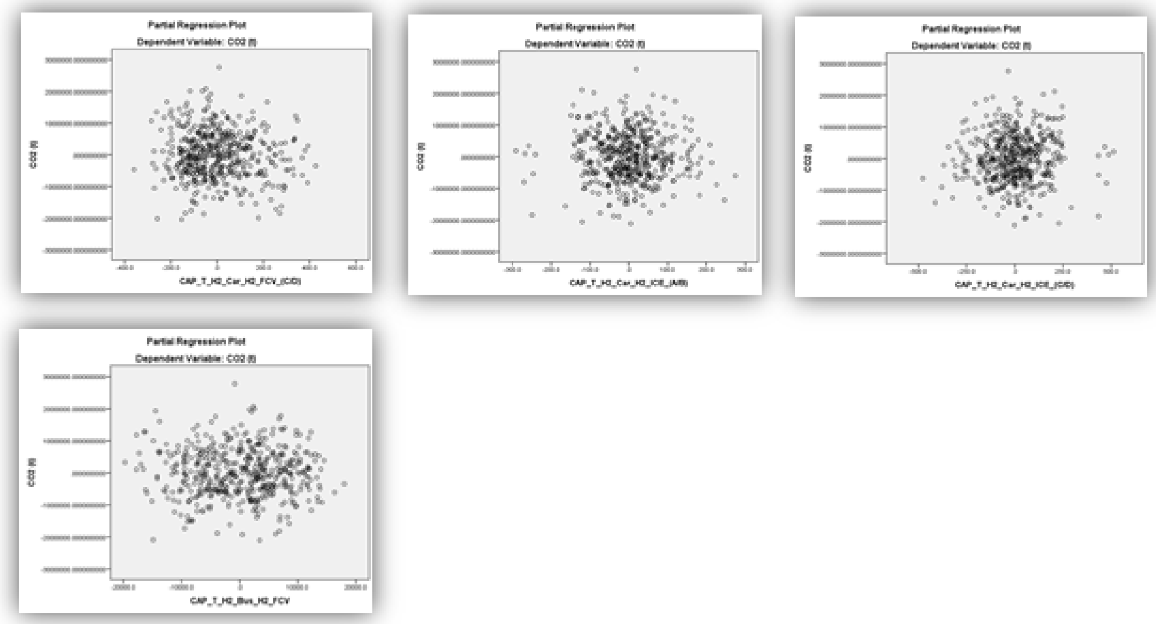


Figure 31. Scatterplots for buildings sector capital costs versus total system emissions, tCO_2

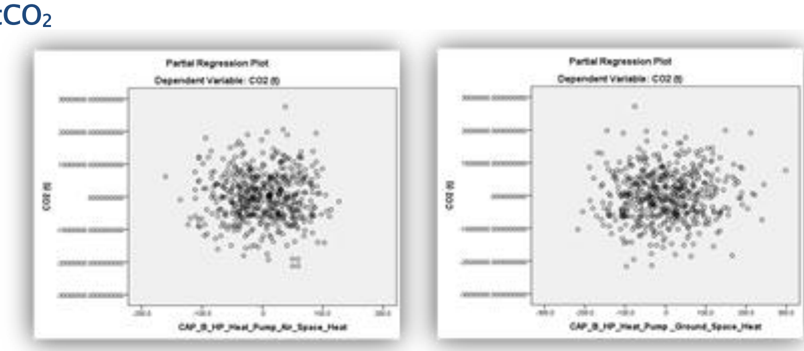


Figure 32. Scatterplot for technology maximum build rates versus total system emissions, tCO_2

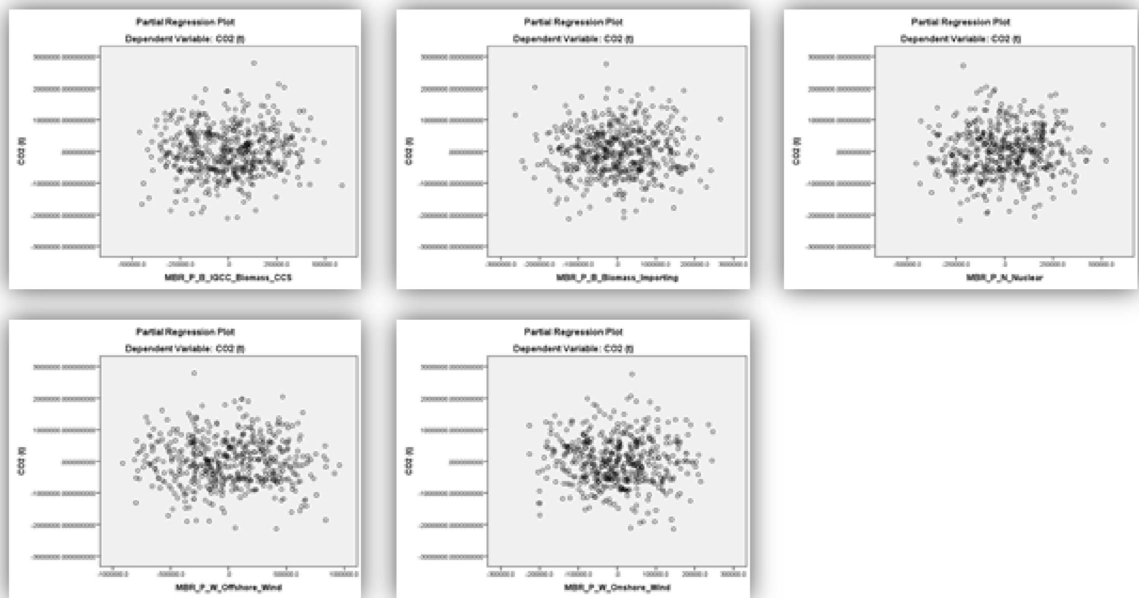


Figure 33. Scatterplot for resources availability versus total system emissions, tCO_2

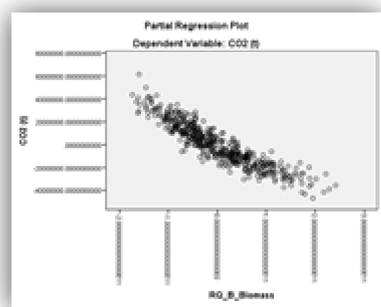


Figure 34. Scatterplots for resources costs versus total system emissions, tCO_2