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Critical mid-term uncertainties in long-term decarbonisation pathways

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ABSTRACT

Over the next decade, large energy investments are required in the UK to meet growing energy service demands and legally binding emission targets under a pioneering policy agenda. These are necessary despite deep mid-term (2025–2030) uncertainties over which national policy makers have little control. We investigate the effect of two critical mid-term uncertainties on optimal near-term investment decisions using a two-stage stochastic energy system model.

The results show that where future fossil fuel prices are uncertain: (i) the near term hedging strategy to 2030 differs from any one deterministic fuel price scenario and is structurally dissimilar to a simple 'average' of the deterministic scenarios, and (ii) multiple recourse strategies from 2030 are perturbed by path dependencies caused by hedging investments. Evaluating the uncertainty under a decarbonisation agenda shows that fossil fuel price uncertainty is very expensive at around £20 billion. The addition of novel mitigation options reduces the value of fossil fuel price uncertainty to £11 billion. Uncertain biomass import availability shows a much lower value of uncertainty at £300 million.

This paper reveals the complex relationship between the flexibility of the energy system and mitigating the costs of uncertainty due to the path-dependencies caused by the long-life times of both infrastructures and generation technologies.

1. Introduction

1.1. Context

As the international scientific and governance communities reach a consensus that climate change presents a severe barrier to future human well-being and livelihoods, the UK continues to legislate for ambitious decarbonisation targets (Climate Change Act, 2008). The UK target is an 80% reduction in greenhouse gas emissions (GHG) below 1990 levels by 2050, excluding international aviation and shipping. This can be equated to a 90% reduction in energy related CO_2 emissions given the uncertainties in mitigation potential of non-CO_2 and non-energy related emissions (Usher and Strachan, 2010). This UK action is consistent with meeting an equal per capita emissions target by 2050 (Committee on Climate Change, 2008), to reduce the probability of exceeding a 2 °C increase in average global temperature over pre-industrial periods (Allen et al., 2009).

The use of bottom-up, technologically detailed energy system models, such as UK MARKAL, continues to play an important supporting role in UK policymaking following an iterative process of development (Strachan et al., 2008). The results of these studies showed that meeting an 80% reduction in GHGs in the UK is both technologically feasible and affordable. UK MARKAL was first developed for, and contributed to, the 2003 Energy White Paper (DTI, 2003) and, with funding from the UK Energy Research Centre, was extended for further projects to incorporate a macro-economic function (Strachan and Kannan, 2007) or compute a partial-equilibrium in MARKAL Elastic Demand (Strachan, 2010).

A typical analysis using an energy system model involves the development of multiple, internally consistent and plausible scenarios. While a powerful method for obtaining insights, the sheer number of scenarios may give conflicting and confusing messages to policy makers because near-term decisions can be mutually exclusive. Furthermore, uncertainties are examined through sensitivity analyses, which add to the number of scenarios. Sensitivity analysis is rarely performed in a parametric fashion, and so interaction between uncertain variables is not captured.

1.2. Literature review

Previous studies have failed to address the significant uncertainties surrounding many aspects of the transition to a low-carbon future in an integrated and systematic manner. This is (i) a problem of applying a deterministic methodology to a complex and multi-faceted problem that is inherently uncertain, and (ii) an issue with the focus on pathways and technologies rather than the uncertainties. There is recognition that the implementation of uncertainty in optimisation

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models, especially for those that rely on scenario analysis, is currently limited (Wallace and Ziemba, 2005).

The majority of modelling studies concentrate on input data uncertainty only (see for example Edenhofer et al., 2010; Clarke et al., 2009; Grubb et al., 2006). In contrast, Edenhofer et al. (2006) make a partial categorisation of uncertainty into parameter (input data) uncertainty and model (structural) uncertainty. Beven (2009) describes uncertainty in a more complete manner, as epistemic—that which can be reduced through learning and aleatory—truly random.

Responses to uncertainty range from Knopf et al. (2010) who recommend that choice and a broad technology portfolio provide hedges against uncertainty and 'limit…known risks' whereas Stern (2006) argues for more demanding long-term policy under uncertainty given asymmetrical costs versus benefits.

Within energy system models based on an optimisation paradigm, a few studies have specifically focussed on uncertainties in the energy system. These used early versions of stochastic MARKAL (Kanudia and Loulou, 1999; Condevaux-Lanloy and Fragniere, 2000; Hu and Hobbs, 2010; Loulou et al., 2009; Labriet et al., 2008, 2010; Loulou and Kanudia, 1999; Kanudia, 1998) and a stochastic version of MESSAGE (Messner, 1996). Hu and Hobbs (2010) give an overview of stochastic MARKAL developments. Early uncertainty work using MARKAL used both an expected-cost criterion (Kanudia, 1998) and Minimax Regret criterion (Loulou and Kanudia, 1999). Studies conducted since have used an expected-cost criterion and have focussed on carbon taxation, demand side management, economic growth, nuclear plant availability and carbon mitigation policies or measures. Hu and Hobbs (2010) examine uncertain CO_2 mitigation, natural gas prices and electricity demand growth under multi-pollutant policies, focussing on the electricity sector. Recently, studies using a multi-region, global incarnation of TIMES, the successor to MARKAL, have emerged. Using stochastic TIMES, Labriet et al. (2010, 2008) and Loulou et al. (2009) present preliminary insights from treating the climate sensitivity parameter as a random variable using a two-stage stochastic framework.

1.3. Research aims

In response to the above concerns, we develop a stochastic version of UK MARKAL to explore the effect of key uncertainties on the UK energy system. We present the research that evolved from work which underpinned a major new policy study (Committee on Climate Change, 2010), with particular reference to the examination of critical mid-term uncertainties for the UK including fossil fuel prices and biomass availability. Indeed, the focus on uncertainties sets this work apart from previous studies on energy system transitions. It builds on insights that are recognisable from previous work, such as electrification of transport and decarbonisation of the electricity system, to consider the interactions between uncertainty and flexibility of a system under transition. This extends the discussion of how best to meet climate reduction targets, by recognising the value of near-term decisions that are robust under uncertainty. This work is timely, notably as the UK Government has implemented an option to review the level of mitigation effort in 2014 if policy at EU and global level does not match UK ambition (HM Government, 2011). The insights from this work are also of interest to the international community: the UK is the first country to legislate mid-term emissions targets, an approach that other developed countries will need to follow to meet long-term targets.

1.4. Layout of paper

Section 2 describes the methodological details of stochastic MARKAL. We describe a useful metric, EVPI, which allows valuation and comparison of uncertainties. We then present a brief rationale for selection of key uncertainties. The results of the subsequent modelling are presented in Section 3. The paper concludes with a discussion in Section 4.

2. Methodology

2.1. Uncertainty in energy system models

Typically, users of deterministic models will assess uncertainty through a sensitivity analysis. These analyses give an indication of the sensitivity of a model's outputs (e.g. system costs) to a variation in data input values (e.g. fossil fuel price). A parametric sensitivity analysis furthers this by exploring interaction between ranges of multiple data inputs. However, a sensitivity analysis does not give any indication of the likelihood that an input or subsequent model output will take a particular value.

Furthermore, in energy system modelling, changing a model input value might result in a different pattern of investment, internally consistent, but contradictory when compared to an alternative input value, the so called 'knife edge' switching especially prevalent in optimisation models (Messner, 1996).

There is a need to move beyond sensitivity analysis when considering epistemic uncertainties. This is because (i) the process of sensitivity analysis does not allow for the probability of an input value to be quantified, (ii) the generation of many contradictory sensitivity scenarios does not result in clear near-term policy-relevant insights, and (iii) the cost of uncertainty remains unknown—there are therefore no means by which uncertainties can be ranked in importance.

Moving beyond sensitivity analysis necessitates considering alternative model formulations to deterministic modelling approaches. There is also a conflict between the complexity of the current generation of data and time intensive energy system models and the computational tractability of running these models in a fully stochastic manner.

A compromise is to use a two-stage stochastic version of the UK MARKAL model. UK MARKAL is an established, peer-reviewed energy system model of the United Kingdom. Although simple in form, the two-stage stochastic approach limits the computational burden while giving a reasonable degree of insight into the effect of uncertainty on the investment decisions for the UK energy system. It also resolves some of the issues outlined above (i) one near-term strategy is given in the results despite characterising the future as uncertain and (ii) a value can be placed on different uncertainties. However, probabilities must be specified exogenously.

Deterministic models, such as the standard variant of MARKAL, give a single solution for each combination of inputs. Stochastic energy system models relax the assumption of perfect foresight, with the two-stage stochastic MARKAL variant splitting the time horizon into a single near-term hedging strategy and multiple recourse periods, dependent upon the pre-defined number of future possibilities, known as states-of-the-world (SOW).

Stochastic MARKAL minimises the expected cost of a set of probability weighted future SOWs (Loulou et al., 2004). A stochastic model is defined by specifying one or more random variables (while the remainder remain constant) for each of up to nine future SOWs that correspond to the length of the recourse stage. A probability weighting is assigned to each SOW to determine its prior likelihood. The model then computes the best average hedging strategy given then sum of the expected costs in the recourse stage and the hedging stage (see Eq. 1)

$$\text{Minimise } Z = \sum_{w \in W(t)} \sum_{t \in T} C_{t,w}.X_{t,w}.p_{t,w}$$

$$\text{Subject to}: A_{t,w}.X_{t,w} \geq b_{t,w}, \quad \forall t \in T, \forall w \in W(t) \tag{1}$$

where t is the time period, T is the set of all time periods, t^* is the resolution time period, w is the SOW, $W(t)$ is the set of SOWs for time period t. For all t prior to resolution time t^*, $W(t)$ has a single element (stage one). For $t \geq t^*$, $W(t)$ has multiple elements (stage two) to a maximum of 9; $X_{t,w}$ the column vector of decision variables in period t, under scenario w, $C_{t,w}$ is the cost row vector in time period t under scenario w; $p_{t,w}$ is the probability of scenario w in period t; and $p_{t,w}$ is the equal to 1 for all t prior to t^*, and

$$\sum_{w \in W(t)} p_{t,w} = 1$$

for all t. $A_{t,w}$ is the coefficient matrix (single period constraints) in time period t under scenario w, and $b_{t,w}$ is the right-hand-side column vector in time period t, under scenario w.

Investments made in the hedging strategy indicate decisions that are made under uncertainty ''here and now'' while decisions that are delayed until the recourse period indicate those that are best made after uncertainty is resolved—''wait and see'' (Hu and Hobbs, 2010). The period in which uncertainty is 'resolved' can be moved forwards or backwards to explore the effect of hedging stage length on the model solution.

Stochastic programming suffers from the 'curse of dimensionality', whereby the number of SOWs increases according to

$$SOW = n^x \tag{2}$$

where x is the number of random variables and n are the number of discrete values the random variables can take.

This means that the problem size increases faster than the number of dimensions added, quickly resulting in computationally intractable problems. The limitation of stochastic MARKAL to nine SOWs means that the analysis is limited to specifying one uncertain variable with up to 9 discrete future values, two uncertain variables each with three discrete future values, three uncertain variables each with two discrete future values (and a limited number of other permutations).

The outputs from the stochastic model are contingent on the probabilities assigned to each SOW. In this paper, each SOW is given an equal probability weighting, where the sum of the weightings equal one. The rationale for this is the Laplace Criterion of insufficient information—in the absence of certainty we can make an assumption of equal uncertainty as to the outcome (Loulou and Kanudia, 1999).

2.2. Metrics

As well as the hedging and recourse strategies, outputs include various metrics. These allow a value to be placed upon the uncertainties characterised in an individual stochastic model. A useful metric is the expected value of perfect information (EVPI)

$$EVPI = COST_{HEDGE} - \sum_{i=1}^{k} p_i \times COST_{PFi} \tag{3}$$

where $COST_{HEDGE}$ is the cost of the stochastic model. $COST_{PFi}$ is the cost of each deterministic equivalent SOW. p_i is the probability weighting assigned to each deterministic SOW. k is the number of states of the world.

As shown in Eq. (3), we can calculate EVPI by subtracting the expected cost of equivalent deterministic SOWs from the expected cost of the stochastic model weighting the SOWs in an equivalent manner. The EVPI shows the difference in 'cost' between scenarios in which uncertainty is entirely removed, i.e. decisions are made with perfect information and those in which uncertainty is present. Refer to Morgan et al. (1992) for more detail.

To calculate the EVPI, one must first run the deterministic equivalents of the stochastic SOWs—in these, the model optimises under perfect information of a particular SOW of the world i.e. there is 100% certainty of the particular SOW occurring. The value of EVPI must be non-negative, as the weighted average of the expected costs of the equivalent deterministic scenarios are lower than the costs of the stochastic solution, as one constraint is removed (the constraint that, before the uncertainty is resolved, investments have to be the same for all states of the world).

2.3. Model setup and selection of key uncertainties

Table 1 shows a summary of the main assumptions used in the model. All prices are deflated to the year 2000. For this analysis, we include legislated UK energy policies up to the Energy White Paper 2007 (DTI, 2007), notably electricity from renewables must contribute greater than 15% of electricity by 2020 and that the Renewable Transport Fuel Obligation is included (minimum of 3.5% energy content of transport fuels comprised of bio-fuels). For a complete description of the UK MARKAL model, see Kannan et al. (2007) and the model updates contained in Usher and Strachan (2010).

Table 1
Shows a summary of the main assumptions used in the model.

Fossil fuel import price scenarios	2000	2030–2050			
M£/PJ		Low	Central	High	V. high
Oil	4.1	5.5	8.3	11.0	13.7
Gas	1.9	2.8	5.7	7.5	9.2
Coal	0.9	1.0	1.6	2.0	2.6
Cumulative CO_2 constraint		**Biomass import constraint scenarios**			
$MtCO_2$	2000–2050	PJ/annum	2000	2015	2030–2050
80% Pathway (CO_2 only)	19,018	Low	0	0	0
90% Pathway (80% GHG equiv.)	16,678	Central	0	630	1260
Key policies			**Key variables**		
Renewable portfolio standard	15% share of all electricity		Discount rate	3.5%	
Emissions trading scheme	None modelled		Time periods	5 year blocks	
Fuel duty	Differentiated taxes applied to transport fuels		Model horizon	2000–2050	

Constraints on energy related CO_2 emissions are implemented as cumulative equivalents of the annual trajectories published in Committee on Climate Change (2008) that run between 2000 and 2050.

It is important to introduce some temporal flexibility in the model when exploring hedging strategies. For example, preliminary runs showed that under very severe fixed emission trajectories, equivalent to a 90% reduction in energy only CO_2 emissions, the model had very little temporal flexibility and gave hedging strategies that were almost identical to the deterministic scenarios. We therefore use cumulative emissions constraints and a slightly lower emissions target of 80% reduction in CO_2 only to avoid over-constraining the model for the fossil fuel scenarios. Under a cumulative constraint, the timing of emissions can be different to that established under a yearly trajectory. However, for the biomass scenario, a more stringent target of 90% reduction in CO_2 better illustrated the effect of constrained biomass availability. In the latter scenario, we retained the cumulative bound, so the model was again able to choose the optimal trajectory over which to abate emissions.

The selection of key uncertainties for this paper followed an informal process allied to the interests of policy makers within the UK and a deep understanding of those uncertainties to which the UK MARKAL model is particularly sensitive derived from the work contained in Usher and Strachan (2010). In the absence of any formal study that formulates a complete taxonomy of uncertainties affecting the UK energy system, this was deemed satisfactory if only to demonstrate the advantages of using a two-stage stochastic approach compared to a deterministic approach. We make no explicit claim as to the relative importance of these uncertainties compared to all possible uncertainties we could explore in this way. Note however that they are both illustrative and policy relevant.

We investigated two uncertainties, fossil fuel price and biomass import availability. Table 2 lists the related model runs analysed in this paper. For each uncertainty, we ran the energy system model in both deterministic and stochastic modes. In deterministic mode, it is necessary to run the model once for each price (4)/availability (2) scenarios. In stochastic mode, the model is run once and produces as many sets of results as there are price (4)/availability (2) scenarios.

2.3.1. Uncertain fossil fuel prices

Uncertainty surrounding the long-run prices of fossil fuel is severe, as shown by the historical volatility in long-term prices of oil, gas and coal. Resource extraction is typified by its risk profile, reports of remaining resources of oil, gas and coal reserves are typically politicised and data availability is poor. Rapid growth across the world, but especially in the transition and developing economies, mean that demand is increasing rapidly while supplies remain constrained, perhaps temporarily. Recently, new sources of unconventional natural gas have led to lower natural gas prices, while crude oil maintains a high price—indicating a potential decoupling of the gas and oil markets.

This scenario establishes four fossil fuel long-run price SOWs (see Table 1) – a central price, one low and two high price SOWs – in line with projections from Department of Energy and Climate Change (2010). The overall expectation is weighted toward an increase in fossil fuel prices. Given the importance of fossil fuel prices, these SOWs are run to give insights into the interactions between fossil fuel price uncertainty and availability of mitigation options.

To allow comparison with between deterministic and stochastic runs of the model, the change in FF price occurs at a set period in the future – 2030 – with all SOWs following the central FF price projection to 2025. We can then compare the stochastic results, in which a near-term hedging strategy is evident to 2025, and multiple recourse strategies for each FF price scenario run from 2030 to 2050, with each of the four deterministic FF price SOWs.

Table 2
Uncertainty model runs.

Uncertainty	2050 energy CO_2 target	Deterministic	Stochastic
Reference scenario	None	REF	N/A
Fossil fuel prices (low, central, high, very high)	80%	D-CUM-FF-L D-CUM-FF-C D-CUM-FF-H D-CUM-FF-HH	S-CUM-FF-L S-CUM-FF-C S-CUM-FF-H S-CUM-FF-HH
Fossil fuel prices (low, central, high, very high) with novel mitigation options	80%	D-FF-L-FLEX D-FF-C-FLEX D-FF-H-FLEX D-FF-HH-FLEX	S-FF-L-FLEX S-FF-C-FLEX S-FF-H-FLEX S-FF-HH-FLEX
Biomass availability	90%	D-BIO-C-YES D-BIO-C-NO	S-BI-C-YES S-BI-C-NO

2.3.2. Uncertain fossil fuel prices with novel mitigation options

To investigate the effect of increasing mitigation flexibility in the face of uncertain fossil fuel prices, we implement a larger portfolio of mitigation options, notably including bio-methane injection to the gas grid and process carbon capture and storage (CCS) technologies in the industrial sector. Through running equivalent scenarios before and after this development process, it is possible to place an approximate value on these flexible mitigation options, notably through the additional options they give to mitigate emissions.

2.3.3. Uncertain biomass availability

This assessment investigates the optimal near-term hedging strategy given the uncertainty surrounding mid- to long-term availability of sustainable biomass. As shown in Usher and Strachan (2010), the availability of sustainable biomass imports is a key low-carbon vector for the UK, used in biomass CCS, CHP and bio-fuels under stringent low carbon scenarios. However, more research is required to quantify accurately the level of resource available to the UK as imports. By the middle of the 2020s, as international markets develop and regulations and standards are established, it is likely that decision makers will be better informed as to the quantity of sustainable biomass available to the UK.

In this paper, biomass availability follows central projections until 2025 when it bifurcates into a low availability SOW—with no biomass imports available and a central availability SOW—with up to 1200 PJ of biomass imports available (E4Tech, 2009), in addition to domestic biomass production (around 13% of UK primary energy in 2000). Preliminary runs showed that a high availability case was identical to the central case.

In the assessment of biomass import uncertainty, we present a more stringent 90% CO_2 target (C90), consistent with meeting an 80% reduction of greenhouse gases below 1990 levels within the UK territory.

3. Results

Before exploring the effect of including uncertainty, we first analysed the results of a reference scenario, a deterministic scenario with central fuel prices and no carbon target. Establishing a reference scenario plays an important role because the policy assumptions included can contribute to an underestimation of the costs of meeting carbon targets in subsequent emission-constrained runs (Strachan, 2010).

While the results from the reference scenario are significant in terms of establishing the baseline from which we derive the subsequent constrained runs' costs, we do not present detailed results of the reference scenario below, as it is largely tangential to our investigation of uncertainty. See Usher and Strachan (2010) for a description of a similar reference scenario.

We present results from the stochastic model in which we assign equal probabilities to four fossil fuel price SOWs and compare the expected costs with the costs of the reference scenario. We then present the results from adding novel mitigation options to the four FF price SOWs above. Lastly, we present results from stochastic and deterministic models of uncertain biomass import availability. For all runs, we compute the EVPI.

3.1. Reference scenario

The reference scenario portrays a future in which the UK is a significant laggard, lowering its climate policy ambition. However, significant efficiency improvements reduce the cost of delivering energy services across the economy. Final energy demand decreases between 2000 and 2050 due to energy efficiency and conservation measures despite the increase in demand for energy services (see Appendix).

3.2. Uncertain fossil fuel prices

There are both similarities and differences across the stochastic and deterministic models. One similarity is the response of energy service demands to price increases. Demands for energy services respond according to the price elasticities held constant in both stochastic and deterministic models. Under a low FF SOW with a carbon constraint, it is cheaper to deliver energy services than under a high FF SOW. This results in a higher final energy demand, less demand reduction and less conservation and efficiency improvements. Under a high FF scenario, we see the opposite behaviour; with consequently greater demand-reduction and lower final energy (see Fig. 1).

Given that changes in FF price do not occur until 2030, the model is able to anticipate the change to a different fossil fuel price scenario and optimise investments in the early period to compensate. This results in near-term differences between deterministic fossil fuel price scenarios. As fossil fuel prices increase across scenarios, the proportion of primary natural gas decreases while the proportion of primary crude oil and coal increases, coal CCS capacity increases, displacing co-firing CCS capacity. Nuclear, hydro and electricity imports are unaffected by changes in fossil fuel price. Final consumption of heat, through residential district heating, increases as fossil fuel prices increase—more efficient consumption of natural gas via cogeneration is stimulated as fossil fuel prices increase.

Hydrogen plays an important role in decarbonisation of the transport system after 2030. Hydrogen production remains at a similar level in 2050 across all scenarios, but moves increasingly to electrolysis from natural gas-SMR with CCS as fossil fuel prices increase (100 PJ under low FF prices to ~330 PJ under very high FF prices). The difficulty in decarbonising the transport sector, in combination with the economic viability of low-carbon hydrogen under different FF prices, results in an electricity system of different size across scenarios. This in turn influences the level of electrification of other sectors including residential heat.

Under a cumulative emissions target, the model has freedom to choose the period in which it can mitigate emissions. The FF price SOWs demonstrate that higher fossil fuel prices are associated with later and steeper decarbonisation, primarily because co-firing CCS becomes less economically viable in comparison to coal CCS at higher FF prices. In the low FF price scenario, investments in coal CCS and co-firing CCS in 2020 (see Fig. 4) displace unabated coal generation, resulting in much lower CO_2 emissions that other scenarios. Part of this reduction in CO_2 emissions is a price response to the more expensive electricity in 2020–2025. However, this early investment in more expensive low-carbon technology pays off in 2030, when for the remainder of the model horizon CCS technology is very cheap to run due to the low FF price. In this way, a small early sacrifice results in a large future benefit (note that the model uses a low social discount rate of 3.5% and that a higher discount rate would alter this behaviour to favour near-term financial savings).

There are some structural discontinuities between the FF price scenarios that are due to the sensitivity of technology choice to the relative relationship between FF prices as well as the absolute level of FF prices. For example, total CCS use between 2035 and 2050 does not increase linearly between SOWs; the very high and central FF price SOWs sequester less CO_2 than the low and high FF price scenarios. A second example is shown by the low FF price SOW in Figs. 2 and 3, where in 2050 the majority of residential heat demand is met through a combination of low-carbon electricity from co-firing CCS and nuclear generation and final use of natural gas in condensing boilers. This is very different from the other three FF price SOWs where CHP becomes more attractive as FF prices increase, while the proportion of heat

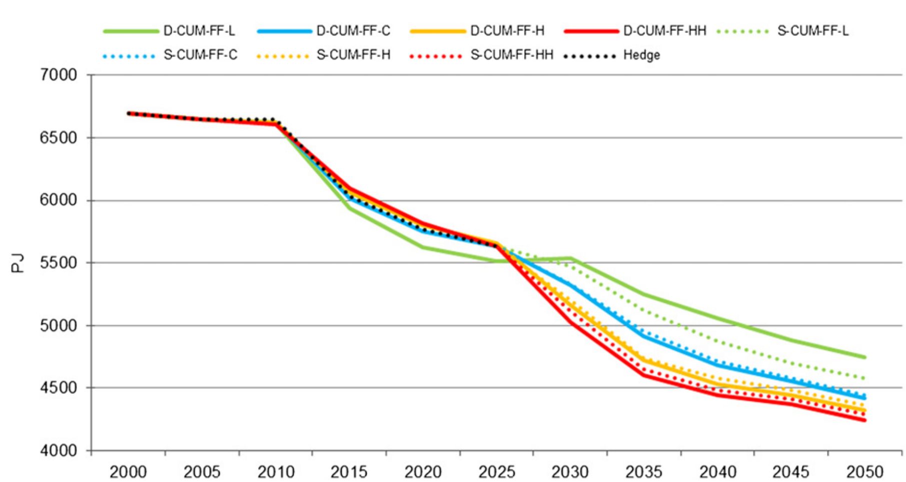

Fig. 1. Final energy of stochastic and deterministic equivalent fossil fuel price scenarios.

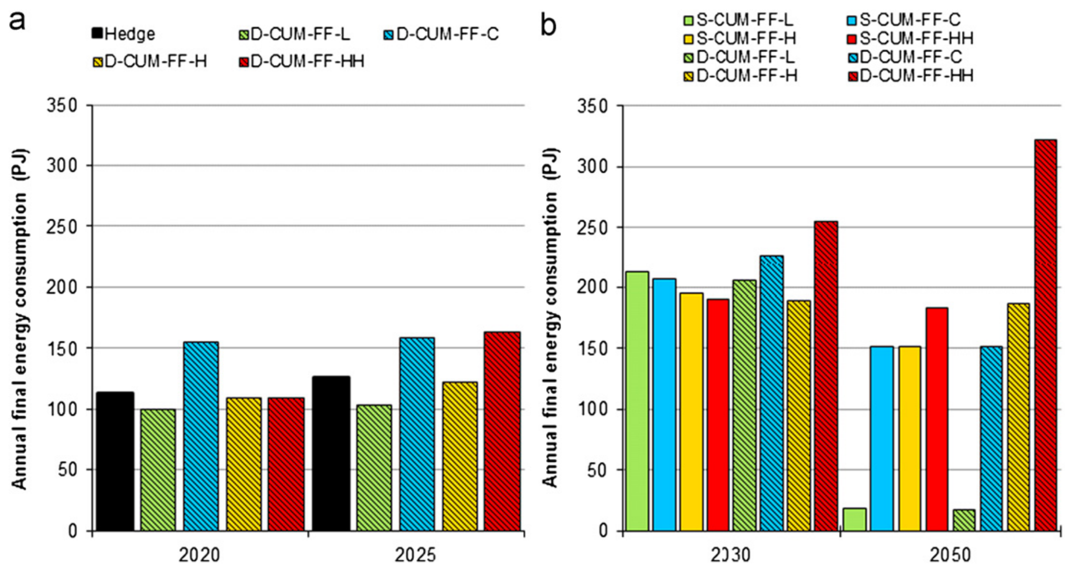

Fig. 2. (a) and (b) show district heating in the residential sector.

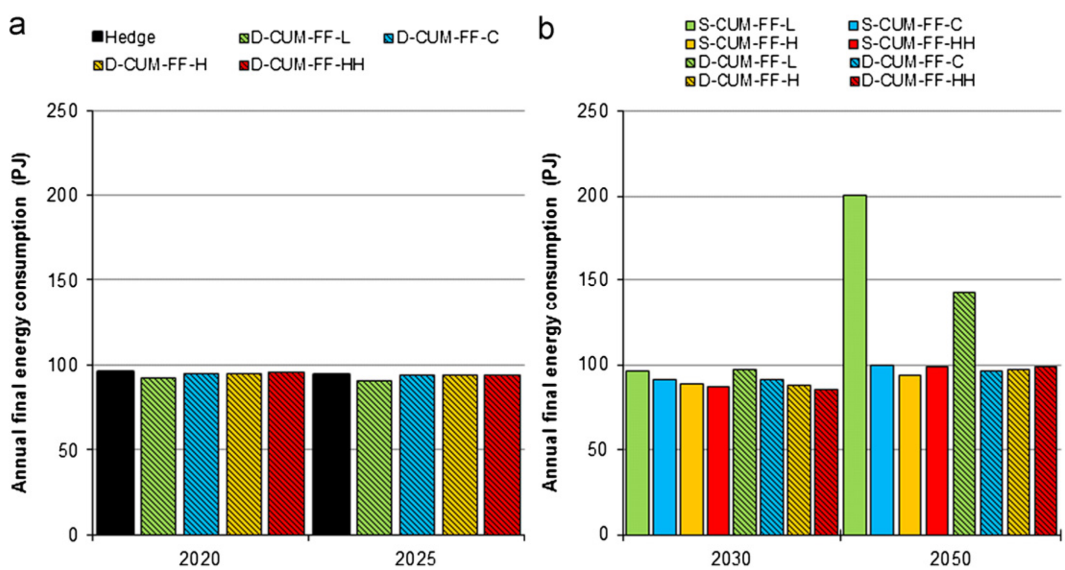

Fig. 3. (a) and (b) show electric heating in the residential sector.

demand met from electricity stays constant. The low FF prices result in a host of other changes not seen in the other scenarios. These include, in 2050, the use of natural gas for heat in the service sector and lower electrification of heat, the majority of hydrogen production from natural gas with CCS, very high use of ($\sim$25 GW) co-firing CCS to generate negative emissions, gas CCS electricity generation and lower levels of nuclear and renewable electricity generation.

The path dependencies and long lifetimes of technologies in the energy system mean that investment decisions that are optimal under a given set of input assumptions could become stranded or lock the energy system into a high-carbon or costly path if those assumptions later change (a naïve scenario). UK MARKAL accounts for technological path dependencies through assigning each technology a lifetime. Therefore, technology investments made in the periods before 2030 (when FF prices change) remain throughout the latter periods.

Conversely, investments in technologies with shorter lifetimes, especially demand technologies such as cars and fridge-freezers, are able to respond more easily to changes in FF prices, or more precisely, the change in structure of the energy system stimulated by the investments due to known future FF prices.

Other areas of flexibility, such as the ability to inject varying levels of bio-fuels into the transport sector, also reduce the cost to the system of uncertain FF prices. For example in 2030, under the very high FF price SOW, imports of almost 300 PJ of bio-fuel (mainly bio-diesel) are used to mitigate the effect of increased oil prices in the transport sector, resulting in a simultaneous decarbonisation of transport. Under a cumulative emissions constraint, this allows an increase in emissions in a different sector or period.

The stochastic hedging scenario presents insights that resolve the following question:

What is the best performing near-term hedge on average, given that different optimal future fossil fuel price SOWs are structurally different and that these structural differences are a result of long-lived near-term technological investments?

Figs. 2 and 3 show how the near-term investments in heating demand technologies of the stochastic hedging strategy and recourse strategies differ from the deterministic SOWs. The hedging investments in district heating in 2025 result in an altered pattern of district heating and electric heating in 2030 and 2050. In the case of electric heating, there is much higher annual energy consumption in the low FF price SOW in 2050 instead of district heating. By 2050, the structure of the residential heating sectors across recourse strategies are similar (compare the solid and hashed bars) but not the same. The different investments made in the hedging strategy have altered the structure of the energy system, which influences a different pattern of optimal future investment under the four recourse strategies.

Fig. 4 shows the effect of the hedging strategy on co-firing CCS capacity in 2030 and 2050. In the deterministic SOW D-CUM-FF-HH, co-firing CCS capacity from 2020 to 2050 is nil. However, in the stochastic scenario, the hedging strategy of $\sim$7 GW capacity results in this capacity remaining through to 2050 (see S-CUM-FF-C, -H, -HH in Fig. 4b). Under the low FF price SOW (S-CUM-FF-L), investment in co-firing CCS can continue to the same level of $\sim$26 GW by 2050 as in the deterministic low FF price scenario (D-CUM-FF-L). Again, the different investments made in the stochastic hedging strategy have altered the structure of the energy system, which influences a different pattern of optimal future investment under the four recourse strategies than in the deterministic SOWs.

Fig. 5 shows the effect of the hedging strategy on coal CCS capacity in 2030 and 2050. In the stochastic hedge, investments in coal CCS are delayed to 2025, as the efficacy of coal CCS is dependent on the future coal price. It is sub-optimal to invest early in coal CCS if there is a possibility that future coal prices will be low, in which case large investments in co-firing CCS are optimal rather than coal CCS (compare S-CUM-FF-L in Figs. 4b and 5b). In contrast, co-firing CCS investments are the same as in the low and central deterministic scenarios—the model accepts the extra cost of co-firing CCS under future high and very high FF prices. Figs. 4 and 5 illustrate path dependency in both the deterministic scenarios and stochastic scenarios: the high capacity of coal CCS generation in 2025 leads to high capacity in 2030 and 2050. Similarly, early investment in co-firing CCS in 2025 leads to residual capacity remaining through 2030 to 2050.

Compared to a hypothetical naïve strategy (where near-term investment decisions under the expectation of, for example, a low

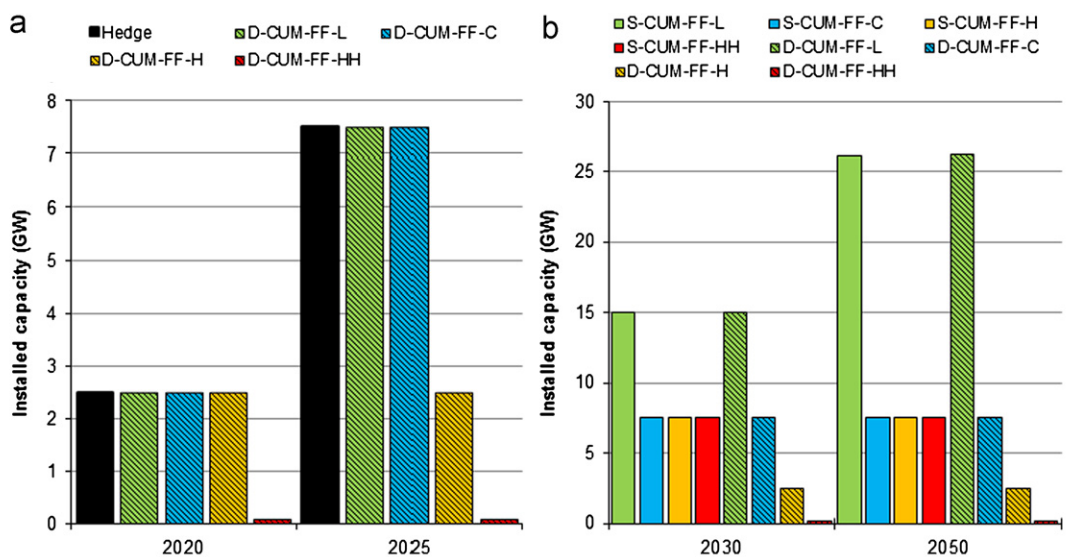

Fig. 4. (a) and (b) show the installed capacity of co-firing CCS.

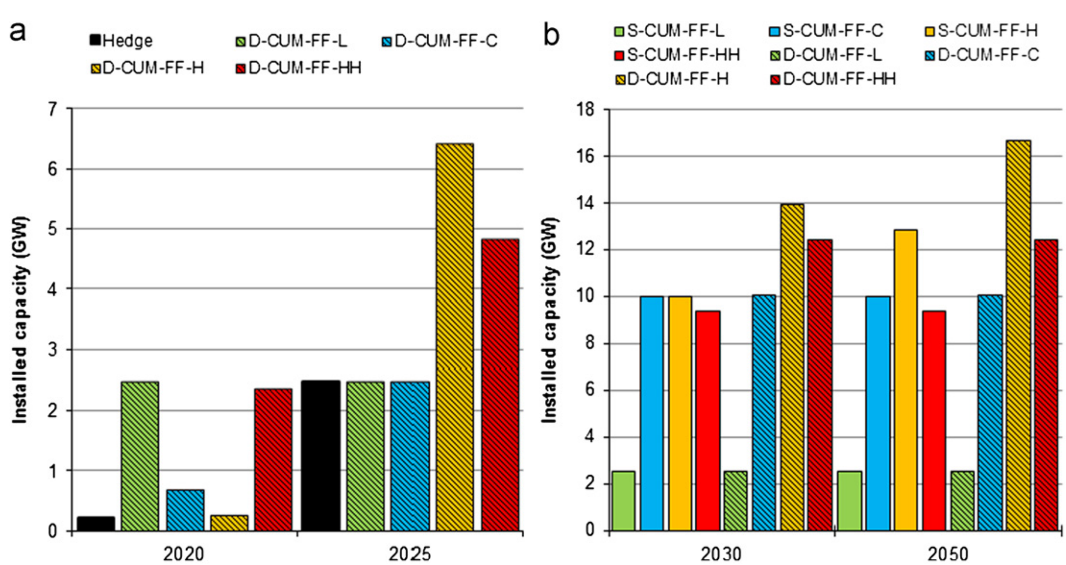

Fig. 5. (a) and (b) show the installed capacity of coal CCS.

fossil fuel price, lock in technologies that would be very expensive under a future high fossil fuel price) an optimal hedging strategy minimises the adverse consequence of near-term investments given the range of future FF price SOWs specified. However, the decision criterion does not include a measure of risk aversion; the hedging strategy is a result of the objective function of minimising the expected cost of the hedging plus weighted cost of the future scenarios.

In contrast to the electricity and residential heat sectors, transport demand technologies generally have short lifetimes. The transport sector is able to react to changes in the fossil fuel prices from the end of the hedging strategy to the new FF price in 2030. Therefore, transport sector recourse strategies look very similar to the optimum deterministic strategies for each FF price SOW.

Despite representing only fossil fuel prices as uncertain, there is no bias evident against fossil fuel technologies in the stochastic hedging and recourse strategies. High investment in alternative technologies such as wind generation is apparent across all SOWs and the investment pattern does not change between deterministic and stochastic SOWs. In both cases, the model waits until 2030 before investing in an extra tranche of wind capacity (again in both stochastic and deterministic SOWs), and this only happens in the very high FF scenario. We see a logical increase in the penetration of renewable generation as fossil fuel prices increase.

The results demonstrate lock-in to an emissions pathway due to the combination of cumulative bound on emissions and identical emissions pathways during the hedging strategy. Until 2025, the timing of emissions in the stochastic scenario is identical to that of the central deterministic FF price scenario, whereas the emissions in the deterministic scenarios vary significantly to 2025 (Fig. 6). This means that the stochastic recourse strategy under each SOW must adhere to a relatively rigid emission pathway from 2030 onwards. The stochastic recourse emissions pathways beyond 2030 then differ little between one another, while those in deterministic runs vary slightly more. However, what little differences there are, now play out as opposite to the deterministic scenarios: the very high FF price scenario (D-CUM-FF-HH) mitigates emission as soon as possible, whereas the low FF price scenario mitigates emissions in the latter periods (D-CUM-FF-L).

3.3. Uncertain fossil fuel prices with novel mitigation options

Running the model with extra novel mitigation options, in this case the option to use grid-injection of bio-methane and industrial process-CCS, enables the energy system to respond more easily to changes in FF price. In this scenario, increasing the number of mitigation options and running with uncertain FF prices results in a smaller difference between deterministic and stochastic strategies.

The addition of industrial process CCS technologies changes the emission trajectory as it becomes significantly easier to mitigate emissions in a previously inflexible (as modelled) sector. This removes pressure from the electricity sector—the previous emphasis on decarbonisation of the electricity sector enabled industry to mitigate emissions through electrification of processes. This becomes more important as the model moves through to the latter part of the model horizon and very stringent CO_2 targets. Deep mitigation in the industrial sector enables all other sectors to mitigate less, through a combination of greater final energy use and less demand reduction. This has significant welfare benefits, which feeds into the objective function. The added flexibility from the industrial CCS option enables the model to respond more effectively to changes in FF prices in the recourse period. For example, under high fossil fuel prices, the model moves towards coal CCS and away from final use of natural gas, whereas under low fossil fuel prices, there is an emphasis on final natural gas consumption.

This addition to the model is a good example of the limited way in which a partially stochastic model, such as UK MARKAL, operates. In this case, the model has perfect information regarding the availability of industrial process CCS after 2030. This certain technology eases near-term mitigation across all scenarios, deterministic and stochastic, increasing the correlation between fossil fuel price scenarios and therefore reducing the cost of uncertainty.

Table 3 shows a summary of the costs for each deterministic scenario and stochastic state of the world, together with the expected cost and Expected Value of Perfect Information (EVPI). The EVPI indicates that in an energy system with fewer mitigation options, the value of perfect information regarding fossil fuel prices is valued at £20.5 billion. However, when more flexible mitigation options are included the EVPI is lower—£11.8 billion, as the system is better able to respond to changing fossil fuel prices.

Under low FF prices, a very large (~£45 billion) welfare benefit is apparent, through importing cheap fossil fuels and avoiding expensive domestic extraction. Least-cost decarbonisation is assisted by the very large early investment in co-firing CCS for low-carbon electricity generation. The stochastic low FF price SOW (S-FF-L-FLEX) is more expensive (£5.6 billion benefit) partly because early investment in CCS technology is lower as shown by

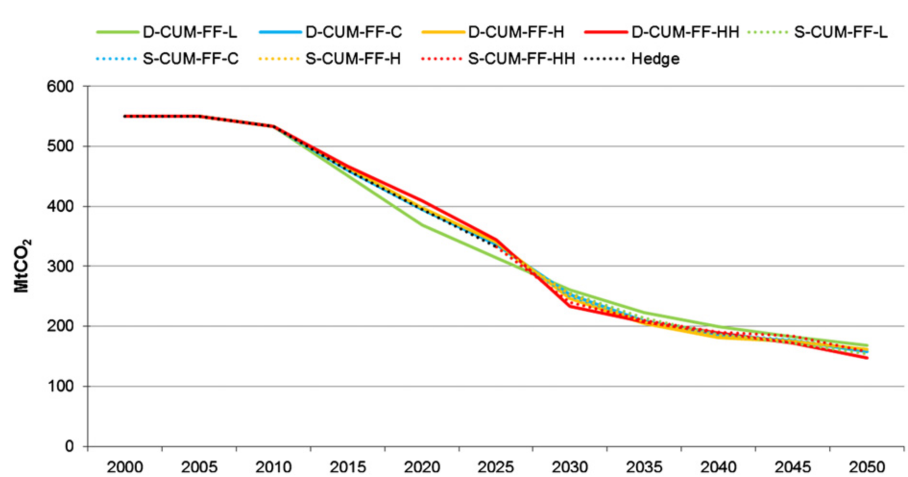

Fig. 6. CO_2 emissions in deterministic and stochastic scenarios.

Table 3
Different in discounted cumulative welfare (2000£B) from the reference scenario.

	Low	Central	High	Very high	Expected	EVPI
Fewer mitigation options						
Deterministic	3.2	67.0	109.8	149.3	82.3	
Stochastic	23.7	86.8	130.0	170.8	102.8	20.5
More mitigation options						
Deterministic	−45.3	58.9	104.1	133.4	62.8	
Stochastic	−5.6	59.0	102.3	142.8	74.6	11.8

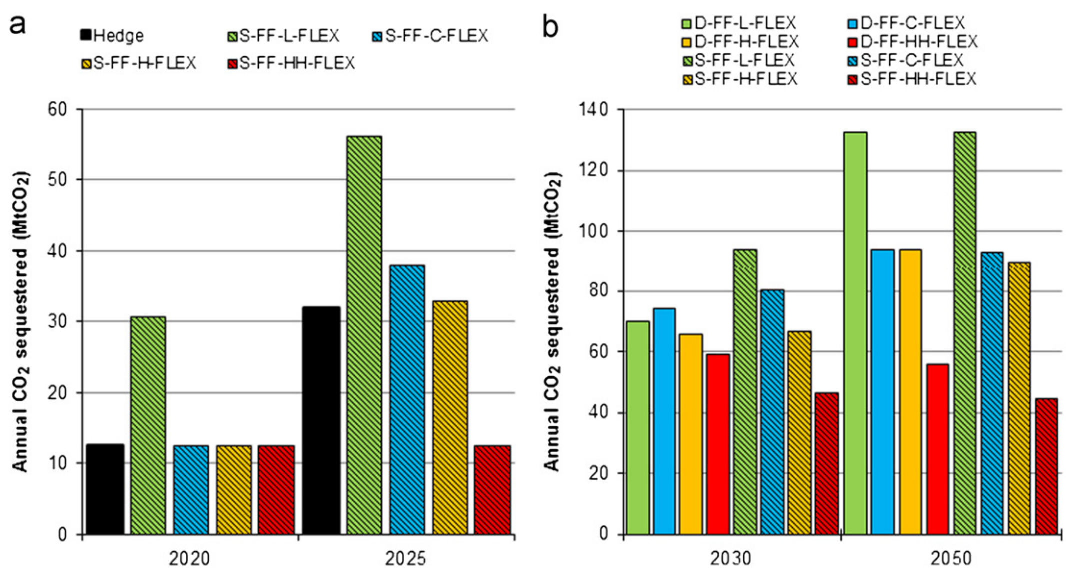

Fig. 7. (a) and (b) show capacity of CCS in the scenario with more mitigation options.

the black column in Fig. 7a. By 2030, as in Fig. 7b, capacity is unable to increase as much as in the deterministic low FF price SOW (D-FF-FLEX-L) due to investment growth constraints, but by 2050, the capacities are almost identical.

3.4. *Uncertain bio-product import availability*

The previous section demonstrated how the use of co-firing CCS as a key low carbon technology changed under different deterministic fuel price scenarios. Co-firing CCS was cost effective under low FF price scenarios, and less so under central and higher FF price scenarios. The majority of biomass used in co-firing CCS was from domestic resources in the early periods. However, biomass imports are converted into bio-fuels, mainly bio-diesel, and for co-firing CCS in the later periods. This is especially the case under higher FF price SOWs, due to the increasing cost competitiveness of alternatives to traditional transport fuels.

In this scenario, we present a more stringent 90% CO_2 target, consistent with meeting an 80% reduction of greenhouse gases below 1990 levels within the UK territory. Under such a severe target, there is a limited pool of technologies that are able to meet projected energy service demands and carbon constraint. The bulk of the effort takes place in the electricity sector, although reduction in energy service demands play an important role by 2050, with higher energy prices influencing changes in the amount of energy consumed, despite moves to a more efficient demand side.

Under central FF prices biomass consumption increases to over 1000 PJ by 2045. An increasing percentage of this is used in co-firing CCS plants (over 40% from 2035 onwards). Note the maximum annual biomass consumption from co-firing CCS is ~600 PJ/annum, equivalent to around 50 GW of co-firing CCS capacity, delivering 50% of total electricity demand in 2050 (total: 2800 PJ) (Table 4).

The dominant low-carbon energy vectors in the transport sector are hydrogen (from electrolysis and gas SMR with CCS), electricity, while bio-fuels fulfil only the requirements for the Renewable Transport Fuel Obligation (RTFO). The remainder of the biomass is used in (i) CHP plants for the delivery of low-carbon district heating to the residential sectors—100 PJ in 2020 to 200 PJ in 2050 and (ii) direct combustion in biomass boilers for residential heating. The annual available domestic production of bio-products rises from ~750 PJ in 2000 to ~1200 PJ in 2050.

The deterministic model results show that constraining biomass imports to zero from 2030 to 2050 increases the welfare cost of the scenario from £149 billion to £155 billion. This is a minor relative change, but shows the very large increase in welfare cost from moving to a more stringent CO_2 target (compare to Table 3). In response, domestic bio-production increases only slightly to ~400 PJ/annum between 2030 and 2050.

There are few differences between the deterministic scenarios in 2025, indicating that the majority of action regarding biomass occurs from 2030 onwards. The largest anticipatory change is a much smaller use of natural gas in the service sector for space and hot water heating. By 2050, the energy systems of the two deterministic scenarios look quite different. Although the electricity system of both increases to around 185 GW, they have different mixes of technology. In the constrained scenario, co-firing CCS capacity is ~31 GW as the limitations on biomass place an upper limit on co-firing capacity, while nuclear capacity increases to ~55 GW. Wind increases to ~28 GW from 21 GW. In the unconstrained scenario, co-firing CCS capacity is ~55 GW

Table 4
Shows consumption of biomass in a central case.

	Year							
	2015	**2020**	**2025**	**2030**	**2035**	**2040**	**2045**	**2050**
PJ								
Primary biomass	323	475	557	670	715	982	1121	1228
% biomass used in co-firing CCS	0	7	17	29	43	45	51	56
No biomass constraint								
Biomass imports	0	0	0	51	113	419	563	679
Domestic biomass production	114	275	339	386	386	386	386	386
Biomass constraint from 2030								
Biomass imports	0	0	0	0	0	0	0	0
Domestic biomass production	212	275	339	432	430	421	414	405

Table 5
Difference in discounted cumulative cost (£B) from the reference scenario.

C90 biomass	Available	Constrained	Expected	EVPI
Deterministic	133.5	138.1	135.8	
Stochastic	134.0	138.3	136.1	0.3370

and nuclear capacity ~30 GW. Investments in either co-firing CCS or nuclear occur from 2030 onwards, and there is no pre-2030 action that reduces the cost of this.

As Table 5 shows, the expected value of perfect information is very much lower than that for the uncertain fossil fuel price scenario (Table 3). The lack of anticipatory action in the deterministic scenarios and their similarity means the resultant stochastic hedging strategy is minor. As biomass use is important only for the post-2030 period under the emission constraint, there are limited near-term investments that are able to mitigate the costs in the recourse. Furthermore, there are alternatives to low-carbon electricity generation using biomass, such as nuclear and renewables, which mitigate the effect of biomass constraints.

4. Discussion

We investigated the effect upon the transition to a low-carbon UK energy system of two major uncertainties over which UK policy makers have little direct control, fossil fuel import prices and biomass import availability. In reality, investors must make decisions in the near-term under a number of uncertainties, including those explored in this paper. A two-stage stochastic energy system model is one method for quantifying how uncertainties affect optimal near-term decision-making.

The results from this study make a clear differentiation between those technologies with long life times that cause path-dependency and those that are not. Under uncertain fossil fuel prices, a crucial role for near-term (2025) investment in co-firing CCS emerged, to the exclusion of coal CCS. However, the optimal hedging investments in co-firing CCS demonstrated significant path dependency and structural adjustments to optimal future energy systems that affect all sectors. This highlighted the important role of short life-span demand technologies that can respond to the structural changes imposed from path-dependent near-term decisions. Large structural changes to the energy system have a limited cost if there is a parallel evolution of flexible technologies across energy demand and supply. This finding supports those of Knopf et al. (2010), who state that a broad technology portfolio, in which technologies are able to adapt to changing conditions, limit risks and enable a greater hedge against uncertainties.

The distinction of uncertainty and technology lifetimes is particularly pertinent for energy infrastructures, as well as generation technologies. Expansion of the electricity network, CO_2 transportation pipelines, EV charging stations and other transport re-fuelling infrastructure, the natural gas pipeline network and hydrogen pipeline networks all play potential enabling roles in a low carbon energy system. Future work should explore the role of long-lived infrastructures under uncertainty, and identify those infrastructures that give flexibility as a response to uncertainty.

The expected value of perfect information (EVPI) is a useful metric because it allows the comparison of scenarios that are constrained in different ways e.g. the value of fossil fuel price uncertainty in a scenario with an 80% CO_2 constraint versus the value of biomass uncertainty under a 90% CO_2 constraint. The results show that fossil fuel price uncertainty is extremely expensive but that this uncertainty can be reduced through the inclusion of novel mitigation options (flexibility). The reason the value of EVPI is so high is due to the divergence of near-term actions between the deterministic scenarios and the optimal hedging strategy. This results in large differences in cost for each fossil fuel price scenario. Changes in fossil fuel price influence the scenario cost directly (the change in cost of imported fossil fuels feeds directly into the objective function) and indirectly (the increase in price of fossil fuels reduces energy service demands). Alternative mitigation options reduce the cost of uncertainty through (i) delaying mitigation by allowing steep emissions in the recourse period to dominate cumulative emissions reductions and (ii) increasing the correlation between scenarios through the certain availability of this additional mitigation.

Care should be taken not to interpret the findings in this paper out of context. The results from UK MARKAL are dependent on the structure of the model and the manner in which the states-of-the-world and associated probabilities are specified. Omitting a possible SOW will result in a different hedging strategy than if all possible future scenarios were included. Changing the probabilities assigned to each SOW will also change the hedging strategy. In this paper, equal weighting was applied to the future scenarios, known as the Laplace Criterion (Raiffa, 1997)—the discrete equivalent of a continuous uniform distribution. This approach results in a conservative measure of 'maximum uncertainty' (EVPI is maximised). As a future extension, we wish to elicit subjective distributions of future uncertain variables.

The assumption of risk neutrality may not represent the interests of a social planner—losses under the high FF price scenario are very high indeed and imply a significant reduction in energy service demands as the cost of delivering of the energy service demands increase. Using a risk-averse objective function would give insights into a near-term strategy that hedge against very large future costs. It is likely that risk-averse hedging strategies would result in quite different near-term strategies, particularly avoidance of fossil fuels and greater adoption of low-carbon technologies. Decarbonisation then has the co-benefit of reducing exposure to fossil fuel uncertainties. Note that by comparing the best and worst outcomes of stochastic and deterministic results, it is possible to gain a first look at the direction of risk-averse investments.

The small number of SOWs permitted in stochastic MARKAL restricts the exploration of uncertainty interactions. These interactions are both interesting and important—for example, under very severe emission targets, bio-products are important for least-cost mitigation, and the destination of bio-products depends on the fossil fuel price e.g. co-firing CCS for electricity, biomass CHP for district heat or bio-fuels for transport. If bio-product availability is also uncertain, the result is a third hedging strategy, the insights from which are greater than the sum of the uncertain FF price and uncertain biomass availability hedging strategies. This is compounded by the so-called 'curse of dimensionality', which places an upper limit on the number of uncertain variables that it are computationally tractable to include in an analysis. This curse is also applicable to the exploding volume of model output, and the analyst, exposed to increasing sets of results. This paper has aimed to provide a compromise between in-depth analysis to tease out the system-wide insights and the wider perspective on two key mid-term uncertainties.

This paper shows that for those uncertain variables that result in divergent near-term actions under perfect information, it is important to make decisions in a manner that take account of the uncertainties, for these uncertainties can be extremely expensive. The results presented in this paper demonstrate the importance

Table A1
Shows the energy service demands in UK MARKAL 3.24.

Demand	Units	2000	2005	2010	2015	2020	2025	2030	2035	2040	2045	2050
Agricultural												
Renewable energy (agro-waste)	PJ	3.0	2.9	2.7	2.6	2.5	2.3	2.2	2.1	2.0	1.9	1.8
Petroleum product (diesel)	PJ	26.5	27.9	29.3	30.8	32.4	34.0	35.7	37.6	39.5	41.5	43.6
Electricity	PJ	15.7	15.7	15.7	15.7	15.7	15.7	15.7	15.7	15.7	15.7	15.7
Coal	PJ	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3
Gas	PJ	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5	5.5
Industrial												
Chemical	PJ	300.7	285.8	291.1	305.7	323.7	330.2	335.9	338.9	342.0	345.1	348.6
Iron & steel	PJ	94.4	93.7	94.8	95.8	96.9	97.9	99.0	99.5	100.0	100.5	101.0
Non-ferrous metals	PJ	31.5	32.3	33.7	35.2	36.8	38.5	40.2	42.0	43.9	45.8	47.9
Other industry	PJ	807.3	801.7	810.5	819.5	828.5	837.7	846.9	846.9	846.9	846.9	846.9
Pulp-paper	PJ	96.3	91.5	93.2	97.9	103.6	106.0	107.5	108.5	109.5	110.5	111.6
Aggregate of non-energy	PJ	525.3	521.7	527.3	533.0	538.8	544.6	550.5	550.5	550.5	550.5	550.5
Residential												
Cooking Hob for existing houses	M.units	25.3	25.2	25.1	25.0	24.9	24.8	24.7	24.6	24.5	24.4	24.3
Cooking Hob for new houses	M.units	0.0	0.9	2.3	3.8	5.2	6.5	7.6	8.6	9.5	10.4	11.3
Cooking Oven for existing houses	M.units	25.3	25.2	25.1	25.0	24.9	24.8	24.7	24.6	24.5	24.4	24.3
Cooking Oven for new houses	M.units	0.0	0.9	2.3	3.8	5.2	6.5	7.6	8.6	9.5	10.4	11.3
Cooling – New	PJ	0.0	5.1	10.1	15.2	20.3	25.3	30.4	35.5	40.5	45.6	50.7
Other electrical appliances for existing house	PJ	114.7	114.3	113.9	113.4	113.0	112.6	112.1	111.7	111.3	110.9	110.4
Other electrical appliances for new house	PJ	0.0	4.5	11.1	18.2	24.9	31.0	36.2	40.9	45.2	49.5	53.8
Chest freezers for existing houses	M.units	4.4	4.4	4.4	4.3	4.3	4.3	4.3	4.3	4.3	4.3	4.2
Chest freezers for new houses	M.units	0.0	0.2	0.4	0.6	0.8	1.0	1.1	1.3	1.4	1.6	1.7
Fridge freezer for existing houses	M.units	15.9	15.9	15.8	15.7	15.7	15.6	15.6	15.5	15.4	15.4	15.3
Fridge freezer for new houses	M.units	0.0	0.6	1.5	2.5	3.4	4.2	4.9	5.6	6.2	6.8	7.3
Upright freezers for existing houses	M.units	6.7	6.6	6.6	6.6	6.6	6.5	6.5	6.5	6.5	6.4	6.4
Upright freezers for new houses	M.units	0.0	0.3	0.7	1.2	1.6	2.0	2.4	2.7	2.9	3.2	3.5
Space heating for existing houses	PJ	827.5	824.4	821.2	818.1	815.0	811.9	808.8	805.7	802.7	799.6	796.6
Space heating for new houses	PJ	0.0	18.9	46.2	76.1	104.2	129.4	151.4	170.9	189.1	207.0	224.9
Water heating for existing houses	PJ	336.9	335.6	334.3	333.1	331.8	330.5	329.3	328.0	326.8	325.5	324.3
Water heating for new houses	PJ	0.0	7.7	18.8	31.0	42.4	52.7	61.6	69.6	77.0	84.3	91.5
Lighting for existing houses	PJ	63.8	63.6	63.3	63.1	62.8	62.6	62.4	62.1	61.9	61.6	61.4
Lighting for new houses	PJ	0.0	2.4	5.9	9.6	13.2	16.4	19.2	21.6	24.0	26.2	28.5
Refrigeration for existing houses	M.units	12.6	12.6	12.5	12.5	12.4	12.4	12.4	12.3	12.3	12.2	12.2
Refrigeration for new houses	M.units	0.0	0.5	1.2	1.9	2.6	3.2	3.8	4.3	4.7	5.2	5.6
Service/commercial												
Cooking	PJ	30.0	30.0	30.0	30.0	30.0	31.0	31.0	31.0	31.0	31.0	31.0
Cooling	PJ	94.0	94.0	110.0	123.0	130.0	138.0	144.0	151.0	158.0	165.0	172.0
Other electrical appliances	PJ	70.0	70.0	73.0	76.0	77.0	78.0	79.0	81.0	82.0	83.0	84.0
Space heating	PJ	377.6	378.0	378.0	378.0	378.0	378.0	378.0	378.0	378.0	378.0	378.0
Hot water	PJ	73.0	73.0	73.0	74.0	74.0	74.0	74.0	74.0	75.0	75.0	75.0
Lighting	PJ	127.0	127.0	129.0	132.0	135.0	137.0	140.0	143.0	146.0	149.0	152.0
Refrigeration	PJ	83.0	83.0	83.0	83.0	83.0	83.0	84.0	84.0	84.0	84.0	84.0
Transport												
Air (domestic) travel	Bv-km	0.1	0.1	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.3	0.3
Bus travel	Bv-km	2.7	2.9	3.1	3.3	3.5	3.7	4.0	4.1	4.1	4.2	4.2
Car travel	Bv-km	358.1	383.2	412.3	443.5	477.0	513.1	552.0	573.6	596.0	619.3	643.5
Rail (freight) travel	Bv-km	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.3	0.3	0.3	0.4
HGV travel	Bv-km	25.9	27.5	29.3	31.3	33.4	35.7	38.1	39.1	40.1	41.2	42.2
LGV travel	Bv-km	47.0	51.5	56.8	62.7	69.2	76.3	84.1	91.4	99.2	107.7	116.9
Rail (passenger) travel	Bv-km	0.4	0.5	0.5	0.5	0.5	0.5	0.6	0.7	0.8	0.8	1.0
Shipping (domestic)	PJ	41.5	40.0	38.6	39.6	40.6	41.6	42.7	43.8	44.9	46.0	47.2
2-wheels travel	Bv-km	4.6	5.1	5.8	6.4	7.0	6.9	6.9	6.7	6.5	6.4	6.2

of understanding the system-wide effect of technologies that have long-life times and exhibit path dependency under uncertainty. Stochastic MARKAL is a powerful tool for investigating the complex systemic dynamics of energy focussed decision-making under uncertainty.

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Appendix

See Table A1.

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