Modelling to generate alternatives: A technique to explore uncertainty in energy-environment-economy models

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Abstract

In this study we describe a novel formulation of the so-called modelling to generate alternatives (MGA) methodology and use it to explore the near cost optimal solution space of the global energy-environment-economy model TIAM-UCL. Our implementation specifically aims to find maximally different global energy system transition pathways and assess the extent of their diversity in the near optimal region. From this we can determine the stability of the results implied by the least cost pathway which in turn allows us to both identify whether there are any consistent insights that emerge across MGA iterations while at the same time highlighting that energy systems that are very similar in cost can look very different. It is critical that the results of such an uncertainty analysis are communicated to policy makers to aid in robust decision making. To demonstrate the technique we apply it to two scenarios, a business as usual (BAU) case and a climate policy run. For the former we find significant variability in primary energy carrier consumption across the MGA iterations which then projects further into the energy system leading to, for example, large differences in the portfolio of fuels used in and emissions from the electricity sector. When imposing a global emissions constraint we find, in general, less variability than the BAU case. Consistent insights do emerge with oil use in transport being a robust finding across all MGA iterations for both scenarios and, in the mitigation case, the electricity sector is seen to reliably decarbonise before transport and industry as total system cost is permitted to increase. Finally, we compare our implementation of MGA to the so-called Hop-Skip-Jump formulation, which also seeks to obtain maximally different solutions, and find that, when applied in the same way, the former identifies more diverse transition pathways than the latter.

Introduction

Avoiding dangerous global climate change, a goal that has recently been reaffirmed by international political agreement at COP21 in Paris as limiting global mean surface temperature rise to well below 2°C above pre-industrial levels[1], is one of the greatest challenges currently facing humanity. Achieving this goal will require large scale changes to the global energy system that serve to mitigate greenhouse gas emissions (Pachauri et al., 2014), and indeed are environmentally sustainable in the wider sense, while at the same time radically enhancing energy equity and maintaining continuity of supply[2].

Assessing specific, global emission trajectories across time, space and sectors is a complex task and models are often used to (1) ensure that what is known about e.g. physical constraints and resource potentials is considered in the analysis, (2) to provide a consistent

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[1] https://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf

[2] http://www.un.org/ga/search/view_doc.asp?symbol=A/RES/70/1&Lang=E

underlying methodological framework for describing the decision making of the key agents and (3) to guarantee the internal consistency of the scenarios. Examples of such long time horizon energy-environment-economy (E3) or integrated assessment models (IAM; note hereafter we use E3 and IAM synonymously) that can provide valuable insight into possible transition pathways which satisfy at least a stylised version of the above mentioned trilemma and as such provide key support to decision makers include e.g. MESSAGE (Messner and Schrattenholzer, 2000; Riahi et al., 2007), IMAGE (Stehfest et al., 2014), REMIND (Bauer et al., 2012) and AIM (Fujino et al., 2006). However, a critical challenge when working with E3 models is appropriately exploring the large uncertainties inherent in the modelling procedure (Peterson, 2006). Without careful elucidation, analysts and policy makers alike can be misled by the precision of the model output and lured into a false sense of security at the certainty of the mechanics of the implied system transition(s) (McDowall et al., 2014).

There are significant uncertainties in not only how the system might develop (see e.g. Smil, 2000; Trutnevyte et al., 2016), but also in how the system is expected to adjust when, for example, fuel prices or emission taxes are altered (Clarke et al., 2012; Pye et al., 2014; Wilkerson et al., 2015). In models, this reaction depends both on the input data assumptions used and the underlying methodology and structure of the model (Kriegler et al., 2015b). Hence, broadly speaking, uncertainty within E3 models stems from two main areas, the adopted input parameter dataset and model structural assumptions/simplifications (see also Dodds et al., 2015).

Taking the former first, E3 models rely heavily on large amounts of input socio-economic, technical and environmental data all of which comes with its own inherent uncertainties, of varying severity, now and into the future (e.g. the evolution of the capital costs of technologies throughout the model's time horizon, for example see Bosetti et al. (2015)). Once the range of uncertainty in each parameter is quantified, a process which itself can be a challenging task, the impact of such parametric uncertainty is often assessed using Monte-Carlo methods, which here we take to include more targeted scenario or sensitivity analyses as well as more general sampling techniques. These function by repeatedly perturbing input parameters in some way, solving the model and generating new realisations of the model's output (see e.g. Usher and Strachan, 2012; Pye et al., 2015; Trutnevyte, 2016). Other approaches, e.g. Messner et al. (1996), Keppo and van der Zwaan (2012) and De Cian and Tavoni (2012), explicitly take parametric uncertainty into account in the decision making process, albeit often in a reduced form, and suggest decisions that are optimal in light of the quantified uncertainties. Finally, sensitivity approaches (e.g. Anderson et al., 2014; Branger et al., 2015; Fais et al., 2016) can be used for analysing and identifying key model sensitivities. Doing this across a range of models (Marangoni et al., 2017) provides another dimension, linking parametric uncertainty with structural (see below).

The other key driver of uncertainty is the model's necessarily simplified representation of the extremely complex real energy-environment-economy system. For instance, such structural uncertainty can originate from methodological assumptions, e.g. energy system optimization with perfect foresight vs descriptive, "myopic" CGE simulation. Model intercomparison (e.g. Knopf et al., 2013; Kriegler et al., 2014, 2015b) and diagnostic (Kriegler et al., 2015a) studies can help to understand the impacts of this form of uncertainty across a portfolio of models, but since their input data is rarely fully harmonised, reflections of structural uncertainty are mixed with those of the parametric kind. Indeed the majority of E3 modelling exercises have focused on the influence of parametric uncertainty, leaving structural uncertainty, and its effects, largely neglected.

In this work we focus on structural uncertainty within a particular type of E3 models, and modelling platforms, that use a specific mathematical formulation common to the field, i.e. those that (usually) seek to minimise total system cost or maximize total consumer and supplier surplus in a linear programming framework (e.g. MESSAGE (Messner and Strubegger, 1995), OSeMOSYS (Howells et al., 2011), TIMES[3] and MARKAL[4]). Such cost optimising, perfect foresight, E3 models generally function in a deterministic way, producing for one run a single cost optimal pathway that meets the set energy service demands subject to any additional constraints that have been imposed on it (e.g. a cumulative greenhouse gas emission budget).

In the last decade studies have begun to address the impact of important structural assumptions within such models including implementing myopic decision making (Hedenus et al., 2006; Keppo and Strubegger, 2010), adding multiple objectives (Alarcon-Rodriguez et al., 2010; McCollum et al., 2011; Mahbub et al., 2016) and, most recently, near cost optimal solutions (DeCarolis, 2011; Trutnevyte, 2013; Trutnevyte and Strachan, 2013; DeCarolis et al., 2015; Trutnevyte, 2016; Li and Trutnevyte, 2017). The latter area of research, which is our focus here, is entirely novel in the context of IAMs and originates from the fact that it is very unlikely that today's, or indeed future, policy makers will function in a purely cost minimising manner (Gigerenzer and Goldstein, 1996), particularly on a global scale, and even if they do, while cost is important it is not the only factor driving decision making (Chang et al., 1982).

Existing studies that have sought to generate near-optimal scenarios have been limited to a national level and have concentrated on one or two key sectors of interest. Here, for the first time, we simultaneously take a multi-sector, global view by adjusting the structural assumption of cost optimality within a complex, global E3 model and exploring the set of feasible solutions that are nearly cost optimal, but maximally different from the original solution in terms of their primary energy portfolio. Furthermore, to achieve this we use a novel, to the energy field, mathematical formulation and go on to compare our method to another technique used previously in the energy literature to generate near-optimal solutions. Such a comparison allows us gain new insight on the relative sensitivities of the two formulations. Beyond the few studies we note above, we are not aware of any others that have used a similar approach in this field and, to the best of our knowledge, this is the first time such a methodology has been applied to an existing, large IAM. In addition, it provides a significantly different route to uncertainty analysis compared to what is currently common in the field and thus could improve the understanding of the scope and nature of the uncertainties present in long term global system transitions.

Exploring the impact of uncertainty associated with structural assumptions or simplifications requires altering the underlying formulation of the optimisation model while keeping its input parameters fixed. In order to relax the key assumption of cost optimality, and map the diversity of different energy systems that lie within its near cost minimum solution space, we use the approach of modelling to generate alternatives (MGA; E. Downey Brill et al. (1982); DeCarolis (2011)). The aim of this is three fold. Firstly, we seek to assess the stability of the results implied by the model's least cost solution and to search for consistent insights that emerge under at least a portion of the full structural uncertainty budget (which here we take to mean the combined impact of all the components of the model's formulation that do not reflect the full complexities of the real world). Secondly, we aim to assess and demonstrate how solutions nearly as good as the original one can look very different and therefore suggest (given the significant real world uncertainties) that even under a given input data set and specific model formulation a wide range of transitions may be considered equally valid. Thirdly, MGA can also be used by the analyst to provide information on possible pathways which may meet additional

[3]http://www.iea-etsap.org/web/Times.asp

[4]http://iea-etsap.org/MrklDoc-I_StdMARKAL.pdf

criteria that decision makers value while at the same time being near least cost, e.g. what would a pathway look like with higher shares of renewables than the cost optimal solution.

In this study we apply MGA, the specific methodology of which will be detailed in a later section, to the TIMES Integrated Assessment Model in University College London (TIAM-UCL), a global E3 model built within the International Energy Agency's Energy Technology System Analysis Program (IEA-ETSAP) TIMES framework. This paper is structured as follows: section 2 describes TIAM-UCL in more detail, section 3 details the MGA implementation used here, section 4 sets out the pair of scenarios that we apply MGA too, section 5 provides a detailed run through of the results and a comparison of our method with another popular MGA approach and, finally, section 6 summarises the insights emerging from this study.

The Model

TIAM-UCL (Anandarajah et al., 2010; Loulou and Labriet, 2008; Loulou, 2008) is a technology rich, bottom-up, cost optimising global energy system focused IAM instantiated within the generic and flexible TIMES model generator General Algebraic Modelling System (GAMS) code. The model aggregates the Earth's countries into 16 regions, each with their own energy system which is represented by technologies (processes) and commodities covering resource extraction/supply of all primary energy sources (e.g. coal, gas, oil, nuclear, biomass and renewables) through conversion and eventually culminating in end-use energy service demand. On the supply side, fossil and biomass resources can be traded between regions while energy service demands are exogenously prescribed at the regional level based on a range of drivers such as GDP, GDP per capita and population. The model runs from its base year of 2005 to 2100, first in 5 year intervals and then after 2050 in 10 year intervals.

The aim of the model is to ensure supply matches demand (i.e. supply = demand) across the energy systems of all regions and for all time-steps simultaneously while minimising total discounted system cost (the objective function) and subject to all specified user constraints (e.g. resource potentials, energy balances, growth constraints). This linear program is solved by the commercial optimiser CPLEX[5]. Due to the computational expense of combining the MGA methodology used here with a large and complicated global E3 model like TIAM-UCL, all runs in this study are carried out from 2005-2050.

Near-optimal solutions

Background

As touched upon previously, cost is clearly a key driver shaping energy system transitions and yet the majority of such systems are made up of many and varied stakeholders who do not have perfect foresight and may have their own objectives and preferences not related to costs (see e.g. Daly et al., 2014; Cayla and Maïzi, 2015; McCollum et al., 2016). It is unlikely that the result of such complex interactions between agents with heterogeneous aims would be, as the conventional normative TIMES approach suggests, transitions that proceed exactly along a cost optimal trajectory. Indeed, studies such as Smil (2000), Trutnevyte et al. (2016) and Trutnevyte (2016) highlight that modelled pathways and historical real-world transitions for a given energy system and period of time can differ substantially. Of course it is also unlikely that energy system transitions would totally disregard cost and so, while not exactly cost optimal, we would expect real-world transitions to be strongly driven by cost considerations.

[5] https://www.ibm.com/software/commerce/optimization/cplex-optimizer/

Recent work using variations of the MGA methodology have found that, for a given model and scenario, small increases in total system cost above that obtained for the optimal case can lead to significantly different solutions (DeCarolis, 2011; Trutnevyte, 2013; Trutnevyte and Strachan, 2013; DeCarolis et al., 2015; Trutnevyte, 2016). That is, solutions that cost just a few percent more than the least cost option can have very different system designs. Thus the typical focus on cost optimality can mask the sizable solution diversity in the near least cost space. Trutnevyte (2016) went a step further and, using ex-post analysis, found that the UK's electricity system transition between 1990-2014 was at least 9% more costly than the cost optimal scenario would suggest over the same time frame, giving some indication of how far real-world transitions can deviate from optimality.

While exploring the near-optimal space of a cost optimisation model such as TIAM-UCL gives a greater understanding of the diversity of plausible energy system configurations, it can lead to some difficulty interpreting and communicating the results as one switches away from a single solution to a set of possible system designs. Furthermore, the diversity of solutions can depend on the specific formulation employed, e.g. mapping the space using variations in primary energy consumption as opposed to final energy consumption for instance. Approaches like MGA also tend to be computationally expensive because they involve running the original model many times with an adjusted, likely more computationally demanding, formulation.

The MGA Method

MGA is a general, catchall term for any method that seeks to sample the near cost optimal solution space of a model and has a number of steps that are, typically, common to all energy system implementations of the technique:

1. The model is solved in standard formulation and a least cost energy system transition pathway obtained.

2. The total system cost of this pathway, scaled up by a small amount or slack (usually $> 1\%$), is entered into the model as a new constraint. Here we use slacks of 1%, 5% and 10%, i.e. the new constraint limits the total system cost of subsequent MGA runs to be at most 1%, 5% or 10% greater than that of the optimal solution. These levels are chosen both to demonstrate the technique and to ensure that solutions produced are, within the context of global, multi-decadal energy system transition, highly comparable in cost terms with the original, cost optimal pathway. We note that although the higher slacks used here are comparable to modelled mitigation costs under climate targets (see Clarke et al., 2014) the deviation of real world transitions away from cost optimality may well be larger still (Trutnevyte, 2016).

3. A new objective function is formulated with the specific aim of exploring the near optimal region defined by the constraint in step 2. This reformulation of the model is also subject to all constraints from the standard formulation in step 1.

In principle, the scope of possible formulations for the new objective function is large and does not necessarily have to be related to the maximization of difference across the model solutions. It could, for instance, maximise the amount of primary energy from wind or minimise the utilisation of certain end-use technologies, with both energy systems being only marginally more expensive than the optimal run. As our focus in this study is finding energy systems that are as diverse as possible and yet still nearly cost optimal, here we use an objective function formulation that searches for a set of transition pathways that are very nearly least cost but also maximally different from one another in terms of the fuel mix of their cumulative primary energy consumption:

$$\text{maximise } \alpha_j$$
$$\text{where } \alpha_j \leq D^{jk} \quad \forall j,k$$
$$D^{jk} = \sum_i |PE_i^j - PE_i^k| \tag{1}$$

$$\text{s.t. } \mathit{tot\_sys\_cost}(PE_i^j) \leq \mathit{optimal\_sys\_cost} \times (1 + \mathit{slack})$$
$$\mathit{slack} \in 1\%, 5\%, 10\%$$

$$\mathit{tot\_sys\_cost} = \sum_{y,r} \left\{ \begin{array}{lll} \text{INVCOST}_{y,r} & +\text{INVTAXSUB}_{y,r} & +\text{INVDECOM}_{y,r}+ \\ \text{FIXCOST}_{y,r} & +\text{FIXTAXSUB}_{y,r} & +\text{SURVCOST}_{y,r}+ \\ \text{VARCOST}_{y,r} & +\text{VARTAXSUB}_{y,r} & \end{array} \right\} - \text{SALVAGE}_r$$

where i is a set that includes all the primary energy carriers considered, i.e. coal, gas, oil, biomass, nuclear, wind, solar, tidal, hydropower and geothermal, PE is the discounted (at the same rate as total system costs) cumulative consumption (summed globally and temporally between 2010-2050) of that primary energy carrier and D^{jk} is the set of L1 or Manhattan distances between this MGA iteration (j) and all previous iterations including the optimal run (k). We use the L1 distance because it can be expressed using a mixed integer formulation and early testing indicated that the most obvious alternative, i.e. a quadratic formulation for L2, was much more computationally intensive and beyond the available computing resources of this study. We do note, however, that different distance metrics may give different results. The cumulative consumption is discounted to limit the benefit afforded to the MGA objective function of difference created by the model towards the end of its time horizon. *tot_sys_cost* is a simplified version[6] (for brevity) of the full total system cost calculation where y and r are the modelled years and regions respectively. Costs are discounted and the terms are as follows: investment costs (INVCOST), investment taxes/subsidies (INVTAXSUB), decommissioning costs (INVDECOM), fixed costs (FIXCOST), fixed taxes/subsidies (FIXTAXSUB), surveillance costs before demolition (SURVCOST), variable costs (VARCOST), variable taxes/subsidies (VARTAXSUB) and finally salvage income generated after the end of the model's time horizon (SALVAGE).

Based on the above formulation the first MGA iteration ($j = 1$) is generated such that its primary energy consumption is maximally different (greatest possible distance) from that used by the optimal run (see Fig 1 for a simplified schematic of a first MGA iteration). For the next MGA iteration the set k includes the optimal and the first MGA iteration and the set D^{jk} now contains two distances, the minimum of which must be maximised. The procedure can then be repeated, each time ensuring that the newly generated scenario is maximally different from all previous pathways. Here we have built our implementation of MGA into the GAMS source code of TIMES using a mixed integer formulation to represent the absolute value expression in equation 1. We note that this particular iterative or sequential approach to MGA has been applied outside the energy and climate field by a number of studies (Loughlin et al., 2001; Zechman and Ranjithan, 2007; Rosenberg, 2015).

In this way the subset of model solutions that exist within the cost space defined by the new constraint added in equation 1 are sampled and a set of radically different pathways obtained. As will be shown, this set of pathways then allows the analyst to begin to understand how stable and robust various features of the energy system transition proposed by the cost minimal solution are by identifying key consistencies across MGA

[6] For further details see `http://iea-etsap.org/docs/Documentation_for_the_TIMES_Model-Part-II_July-2016.pdf`

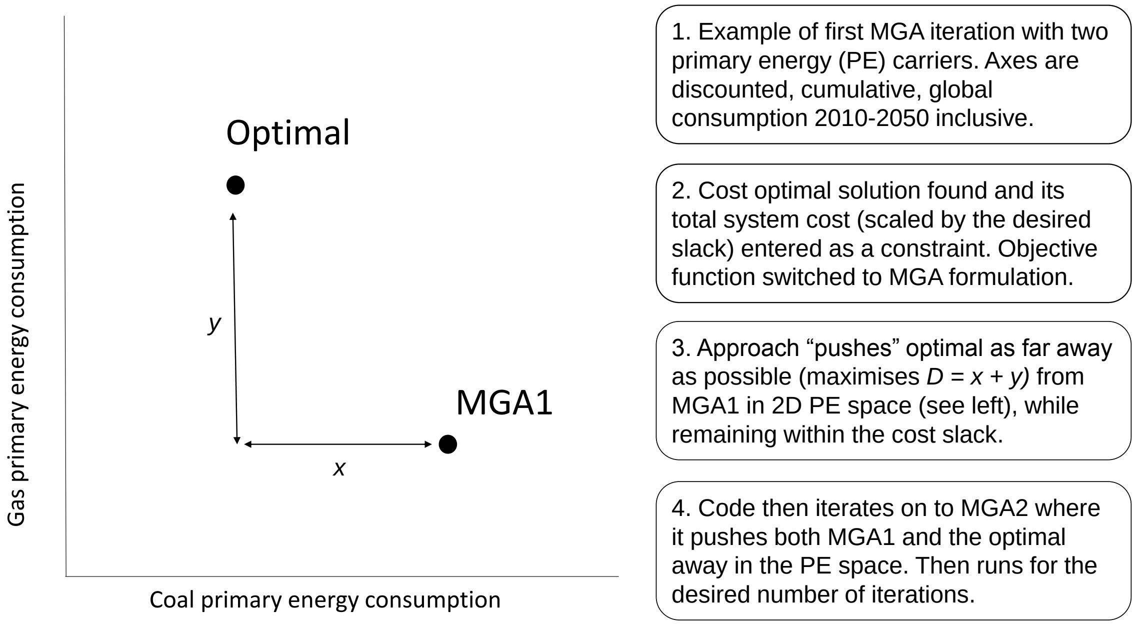

Figure 1: Schematic depicting an example of how the MGA method used in this study proceeds. In this case only two primary energy carriers are shown for diagrammatical simplicity whereas the full implementation uses ten carriers and runs for five iterations.

iterations. Furthermore, it naturally follows that these pathways also provide an indication as to which elements of the original solution can vary significantly within the near optimal space. Such a set of pathways can also begin to facilitate an exploration of additional criteria that may be of interest to decision makers.

The Scenario

The purpose of this study is to describe and then demonstrate the implementation of a form of MGA within a E3 model and to that end we use a version of the TIAM-UCL representation of Shared Socio-economic Pathway 2 (hereafter SSP2). SSPs are a new scenario framework that detail a range of plausible future story lines for the evolution of the global socio-economic system and are being used by the climate change community to carry out research on impacts, adaptation and mitigation (for further details see ONeill et al. (2014)). SSP2 describes a so-called "middle of the road" world with intermediate challenges to mitigation and adaptation with respect to SSP1 and SSP3. Quantitatively, this is implemented in TIAM-UCL using projections of country level population and GDP per capita, provided by the Organisation for Economic Co-operation and Development (OECD)[7] and aggregated to the model's 16 regions, combined with a set of assumptions which are calibrated to the SSP marker models[8] for final energy demand, low carbon technology availability and fossil fuel resource potentials. We consider both a business as usual (BAU) case that doesn't include any explicit climate constraints and a global CO_2 reduction pathway scenario applied to SSP2, i.e. 50% cut relative to 2005 levels by 2050 with emissions peaking in 2015 and linearly declining, roughly consistent with a 2°C temperature rise target.

[7] https://secure.iiasa.ac.at/web-apps/ene/SspDb/static/download/ssp_suplementary%20text.pdf

[8] https://tntcat.iiasa.ac.at/SspDb/dsd?Action=htmlpage&page=about

Results and Discussion

BAU

First we begin by analysing the results from our BAU scenario which are shown in Fig. 2. The top left panel of this figure displays cumulative global primary energy consumption between 2010-2050, i.e. the metric whose difference is maximised between each MGA run and all those previous to it including the least cost solution, for all three MGA slacks (1%, 5% and 10%). At each slack level the results from the optimal run are plotted as the first stacked bar followed by the five MGA iterations. The top right panel of this figure shows the fractional variability of each energy carrier across the MGA runs with respect to the optimal with, for each fuel, the three slacks ordered from left to right as 1% to 10%. Note the variability panel is not a standard box plot but simply reports a maximum and minimum variation over the MGA iterations normalised by the results of the optimal run. From these two plots, it is immediately apparent that sizeable variability is seen for important, i.e. significant shares of total primary energy, fuels such as coal and gas even at 1% slack. The former varies by $\sim \pm$ 50% across the 1% runs while the latter $\sim \pm$ 30% and so we see that just a minor deviation away from the structural assumption of cost optimality leads to a large range in key primary energy carrier consumption under this scenario. That said, by comparison one consistent insight does begin to emerge in terms of oil consumption, which shows comparatively minimal variability at $\sim \pm$ 10%, suggesting that its role in the energy system is less easily replaced by alternatives with similar costs.

Staying with the top two panels of Fig. 2, as the slack level increases the variability of each energy carrier also increases while the pattern of variability discussed above remains largely unchanged. Such a trend of escalating variability with increasing slack is to be expected as the model can push further up a given primary energy carrier's supply curve, and correspondingly reduce the consumption of other carriers to compensate, thus creating more difference across iterations. At the same time, it is also better able to adjust to the resulting knock-on cost implications further into the energy system of doing so. That said, there are two noteworthy exceptions with biomass appearing to hit both upper and lower limits on its consumption at slacks of 5% and 10% and renewables showing significantly asymmetric behaviour as the slack level increases.

The middle and bottom panels of Fig. 2 take a more sectoral view of the outcome of applying MGA to this scenario and allow us to assess how variability at the primary energy level propagates through certain parts of the energy system. The middle left panel shows cumulative global electricity production, again between 2010-2050 with the three slacks plotted as before. From the variability diagram, right middle panel, we see the spread in coal and gas consumption discussed above mapping through to the power sector with the left hand panel showing that these two fuels are, in some cases, substituting for one another. One can also see from this that whereas coal is mostly used for power generation, gas can be used much more flexibly throughout the energy system and therefore its contribution to electricity generation can vary significantly across two iterations that have fairly similar gas use in primary energy. Furthermore, all energy carriers considered show a sizeable range of usage, i.e. $\sim \pm$ 50% or more, even at 1% slack and once more the broad trend of increasing variability with slack is apparent.

The middle panels of Fig. 2 additionally highlight that in some MGA iterations at slacks of 5% and 10% there is an increase in electricity production, relative to the optimal case, typically associated with, although not always (see the third MGA iteration at 10% slack), greater total primary energy consumption. This likely occurs because the MGA implementation used here seeks to maximise difference at the primary energy level and so may choose to increase total primary energy usage. As end-use demands are inelastic in the set up of TIAM-UCL used here, this leads to the model choosing less efficient technologies and to an overall drop in energy efficiency of the system as well as a total system cost

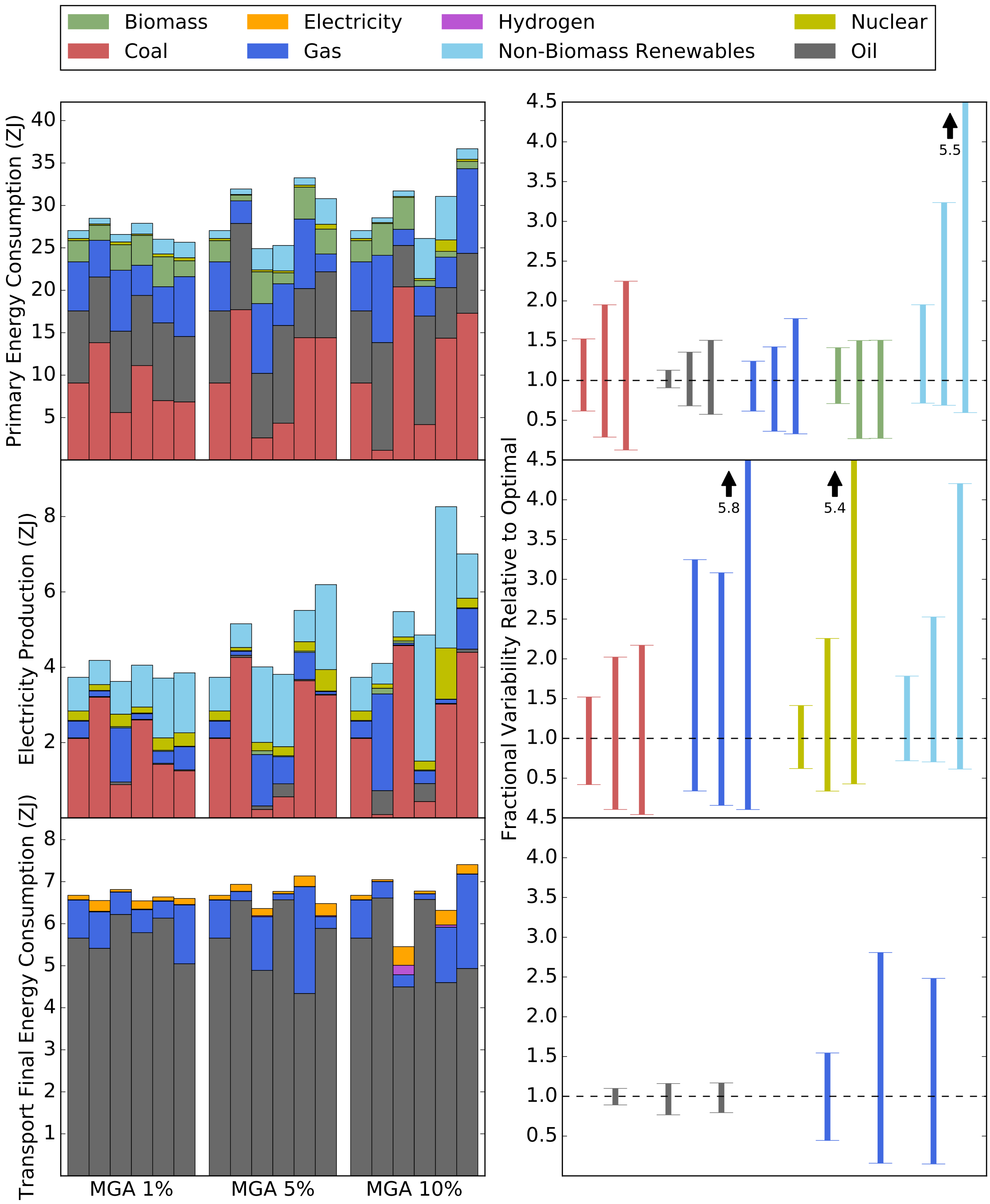

Figure 2: Results from applying MGA to our BAU scenario. The left column shows, from top to bottom, cumulative global primary energy consumption, electricity production and final energy consumption in transport between 2010-2050 (inclusive) for the three different MGA slacks of 1%, 5% and 10%. For each slack the first bar is the cost optimal run followed by five MGA iterations. The right column assesses the fractional variability of each energy carrier across the MGA runs in the corresponding left panel with respect to the optimal. For all carriers the bars are ordered by slack from 1% to 10%. Note that only those fuels that provide greater than 2% of total energy production or consumption in the left panels are shown in the variability plots for the sake of clarity.

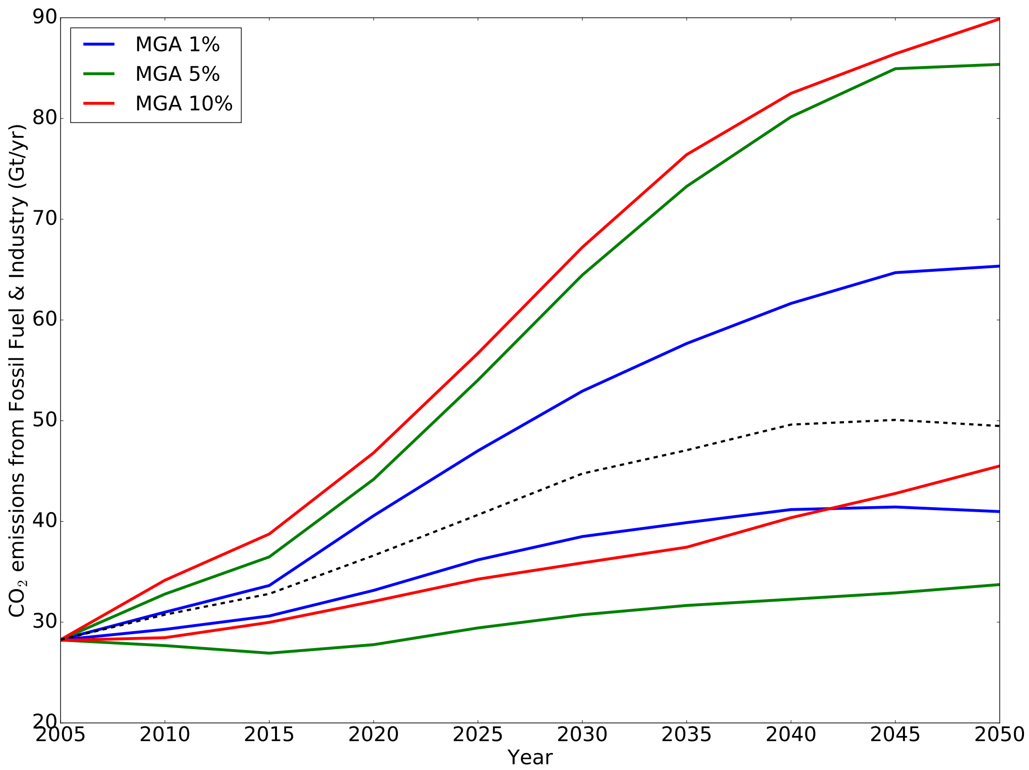

Figure 3: The spread in CO_2 emissions from fossil fuel combustion and industry between 2005 and 2050 for our BAU scenario at the three slack levels considered here. The emissions trajectory for the optimal pathway is plotted as a black dashed line for reference.

increase that the model is better able to afford with rising slack. The model has thus used the slack to replicate an energy efficiency gap (Hirst and Brown, 1990) similar in nature to that which is observed in the real world. Equally, in the case of MGA3 at 10% slack, the model can also choose to *increase* energy system efficiency if it is beneficial in creating difference, again with an associated impact on total system cost.

Moving finally to the bottom pair of panels in Fig. 2, which show final energy consumption in the transport sector by fuel in the same format as discussed previously, we see that, of the two key energy carriers oil and gas, consumption of the former proves to be highly consistent with little increase in variability as slack increases, i.e. to at most $\sim \pm$ 20%. This indicates that this sector continues to rely heavily on oil even when the total system cost is allowed to escalate by up to 10%. It is worth mentioning, however, that this merely suggests that the implied cost curve for creating difference between iterations has higher marginal costs for replacing oil in the transport sector than creating a similar difference elsewhere in the system, not that the 10% cost slack wouldn't be adequate for transforming the transport sector.

Another noteworthy point highlighted by the bottom right panel of Fig. 2 is that it is possible for the variability in consumption of a given energy carrier to be reduced as slack increases for sectors further into the energy system. This, again, is likely a facet of the MGA formulation employed in this study which incentives difference at the primary energy level but gains no benefit from that created at later stages in the system. As a result, while the variability in the consumption of all primary energy carriers is seen to increase monotonically with slack, it need not for all carriers in individual branches of the energy system. For example, viewed through the lens of one particular sector, the model may benefit from further increasing (or decreasing) the usage of a given energy carrier in a different sector as one moves to increasing slacks and so the variability of said carrier in

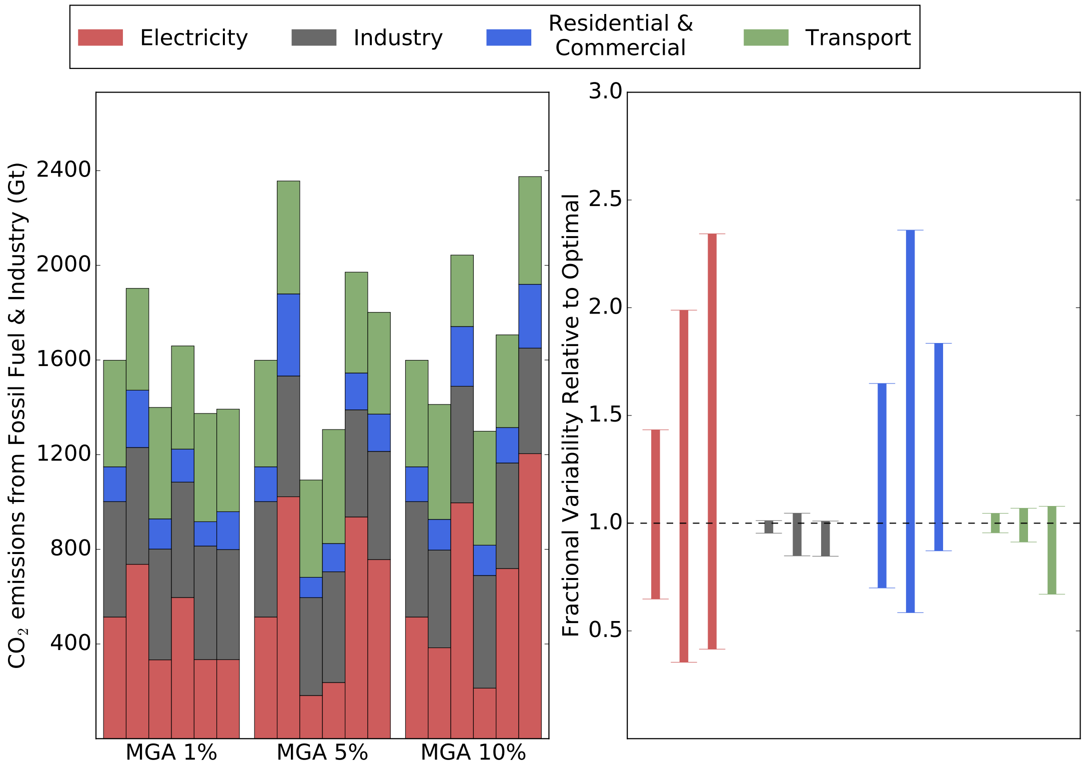

Figure 4: The left panel shows cumulative 2010-2050 CO_2 emissions from fossil fuel combustion and industry by sector and slack. The right panel shows the fractional variability in this variable with the three slacks plotted as before from 1% to 10% left to right.

our chosen sector may stay the same or even decrease as the permitted total system cost grows.

Fig. 3 shows an alternative view of how the variability of energy carrier consumption discussed above impacts the energy system. Here we plot the spread in CO_2 emission trajectories, from fossil fuel combustion and industry between 2010 and 2050, for all MGA iterations at the three slack levels and, for reference, we also include the pathway obtained from the cost optimal run. Immediately it is clear that even at 1% slack the spread in emissions is large, e.g. $\pm$ 10 Gt/yr or more in 2050, and grows substantially as the model is less cost constrained, e.g. at 10% slack emissions can almost double in 2050 with respect to the cost optimal run. This variability is driven by the extensive spread in coal and gas use presented in Fig. 2, with some iterations relying heavily on the former and others, e.g. MGA3 at 10% slack, reducing both at the primary energy level and almost entirely substituting them out for renewables in the electricity sector. To elaborate further on this point, in Fig. 4 we show cumulative CO_2 emissions between 2010 and 2050 for each sector by slack and their range relative to the optimal run. Here we see that the spread in emission trajectories stems primarily from the electricity sector, with its large relative and absolute variability, and, to a lesser extent the residential and commercial sectors with industry and transport showing very little change in variability with increasing slack. Put another way, this implies that it is more cost effective for the model to create difference at the primary energy level by altering the consumption of energy carriers from one iteration to the next in the former three sectors than in the latter pair.

A final point of interest from Fig. 3 is that, while a 10% slack iteration results in the largest absolute emissions, 5% seems to capture more variability across almost all years. Again this is likely an outcome of our specific MGA methodology, i.e. that it seeks to maximise difference between iterations in terms of cumulative primary energy use and not

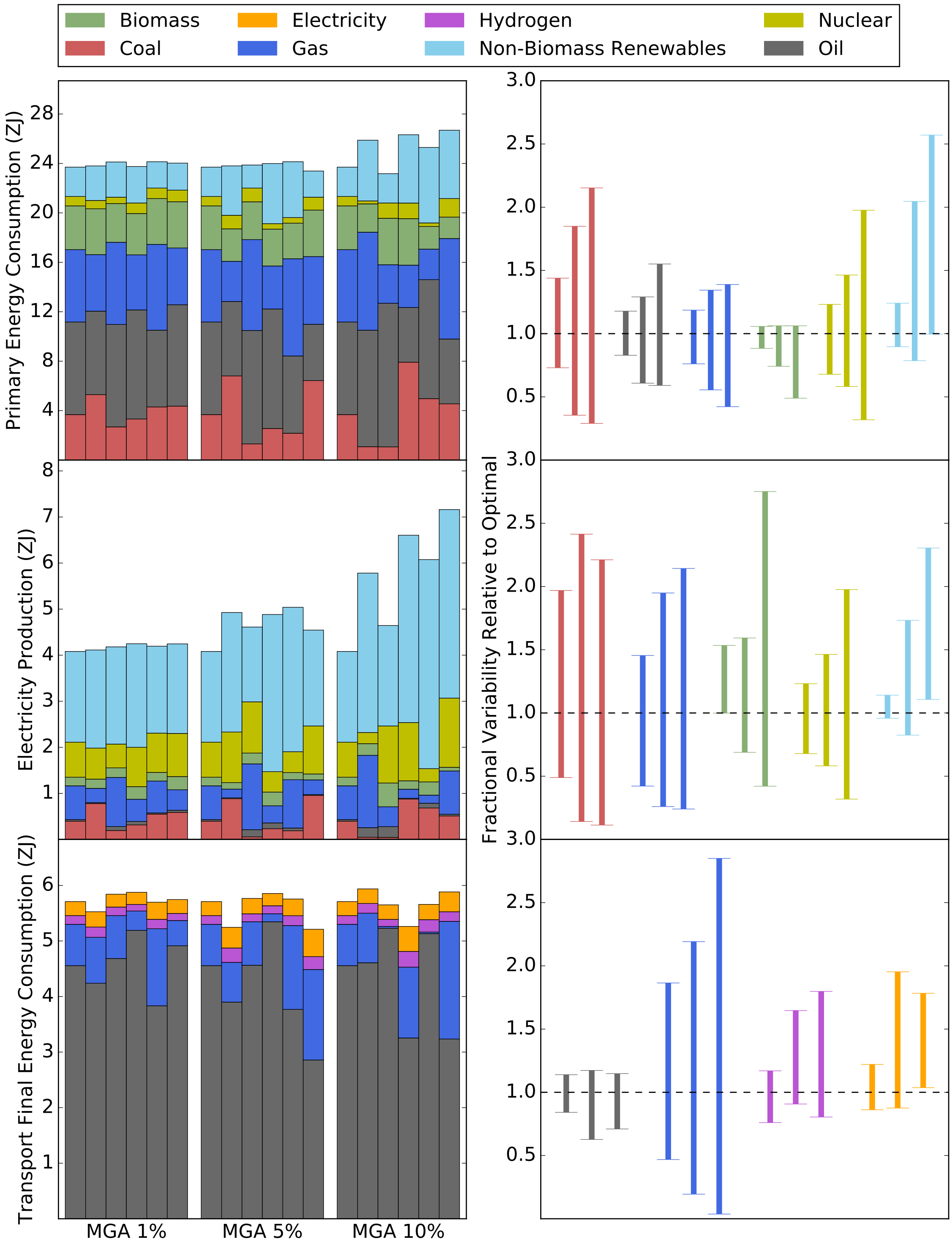

Figure 5: Results from applying MGA to our 50% CO_2 reduction by 2050 scenario. The layout of the figure is identical to Fig. 2.

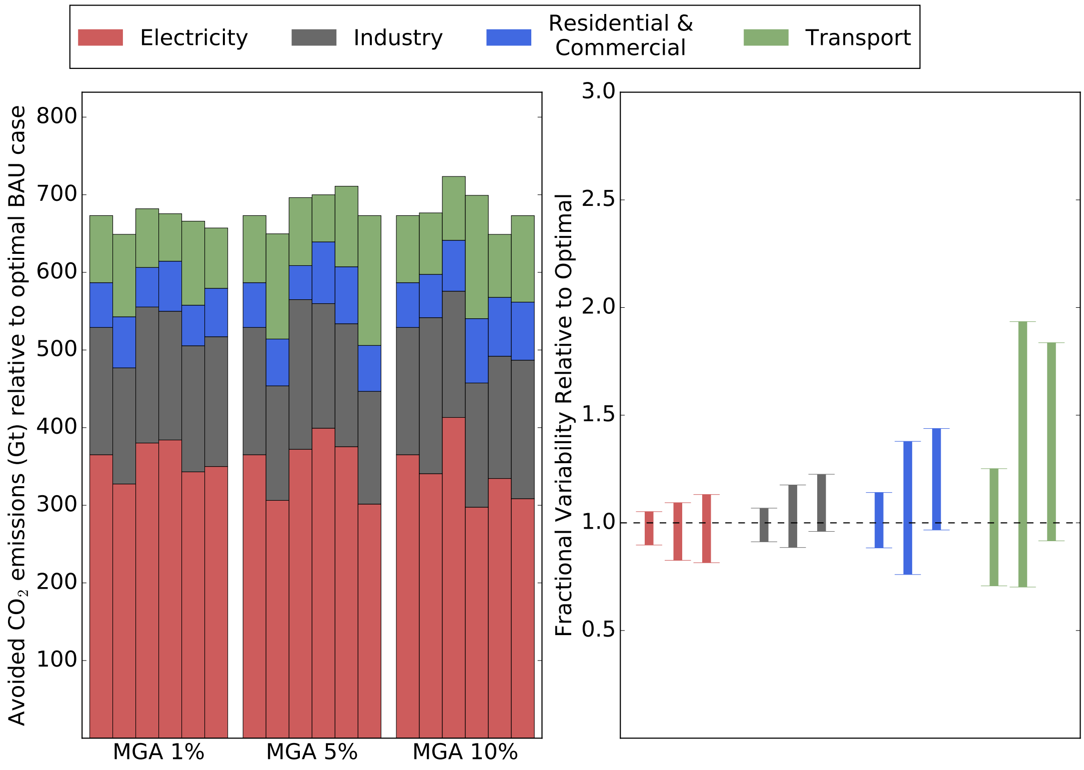

Figure 6: The left panel shows cumulative (2010-2050) avoided CO_2 emissions relative to the BAU optimal case by sector and slack. Again, the right panel shows the relative variability of these parameters with respect to that of the optimal mitigation case, from 1% to 10% slack left to right.

CO_2 emissions.

To summarise, in this section we have demonstrated that applying a range of relatively small cost slacks to our BAU scenario and seeking to map the diversity of solutions within that cost space leads to significant variability around the optimal solution's results throughout the energy system. We have also seen that this variability increases as greater total system costs are permitted, at least up to a slack of 10%. Put another way, these results highlight how certain parts of the optimal solution are very sensitive to fairly minor alterations in this part of the model's structure, thus indicating that, in light of the numerous real world uncertainties, a range of "equally good" and very different transition trajectories exist. Conversely, certain elements of the model solution are fairly robust across the iterations and suggest that an alternative development is less likely to be nearly as cost effective as that proposed by the optimal solution (e.g. oil use in transport). It is, however, worth noting that the results shown here assume no emission constraint or tax of any kind and the model therefore has more flexibility to determine the fuel mix than it would if such a constraint was imposed. We'll explore this in the next section.

50% CO_2 reduction

Next we move on to examining how a small deviation from the structural assumption of cost optimality impacts our mitigation scenario. Fig. 5 displays the results for the optimal run and five MGA iterations at each slack level in the same format as Fig. 2. Straight away it is evident that for the majority of energy carriers across the three pairs of panels in the former figure there is less relative variability than in the latter case. As previously mentioned, this occurs because in this scenario the model is constrained by the applied CO_2 reduction pathway and so the diversity of primary energy mixes in the near cost optimal solution space is reduced relative to the BAU case.

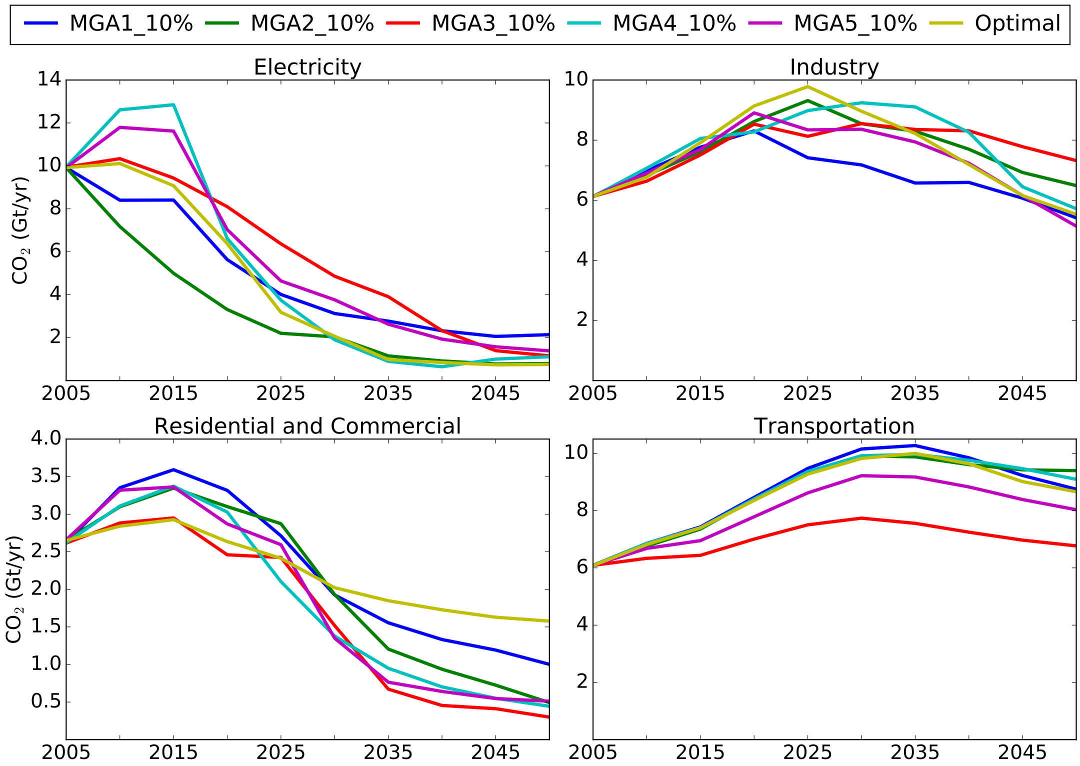

Figure 7: Sectoral CO_2 emission trajectories for the 10% slack and optimal mitigation runs.

In primary energy terms, at 1% slack particularly consistent results stand out for oil, biomass and renewables with coal use showing the most sizeable range, i.e. $\sim$ +50% to $\sim$ -25%. Again this pattern remains fairly consistent as the total system cost constraint is increased with the same two notable exceptions. Specifically, once more biomass seems to hit an upper usage constraint while renewables is seen to be increasingly asymmetric with growing slack, i.e. the model favours significant up-ticks in consumption, relative to the optimal run, and only very limited decreases over the MGA iterations. In the power sector, renewables and nuclear are the main contributors and are also the two most consistent fuels across the slacks. Furthermore, Fig. 6 and 7 indicate that the near complete decarbonisation of the electricity system by 2050 is a robust finding across all MGA iterations and slacks, with sectoral emissions dropping by $\sim$ 79-93% relative to 2005 levels. In the transport sector, the spread in oil use is again small ($\sim$ +10% to $\sim$ -25%) even as the permitted total system cost grows indicating consistency in the common narrative (e.g. Knopf et al., 2013; van der Zwaan et al., 2013) that electricity generation would be expected to decarbonise before transport when the energy system is responding to mitigation targets.

Fig. 6 shows that, from a cumulative perspective, the absolute sectoral variation in avoided emissions with respect to the optimal BAU case is at most $\sim$ +80 $GtCO_2$ to $\sim$ -50 $GtCO_2$. This implies that, as touched upon above, the mitigation burden is distributed fairly consistently across sectors throughout the iterations and slacks. That said, Fig. 7 demonstrates that, taking the 10% slack cases as an example, there is more variation in the sectoral emission trajectories over time than perhaps would be expected from Fig. 6, e.g. see MGA3's transport emissions which are $\sim$ 3 $GtCO_2$/yr less than the optimal run from $\sim$ 2030 onwards.

However, the general message from the mitigation scenario is, as expected, that once an emission constraint is added, a given cost tolerance (slack) allows for less variation than

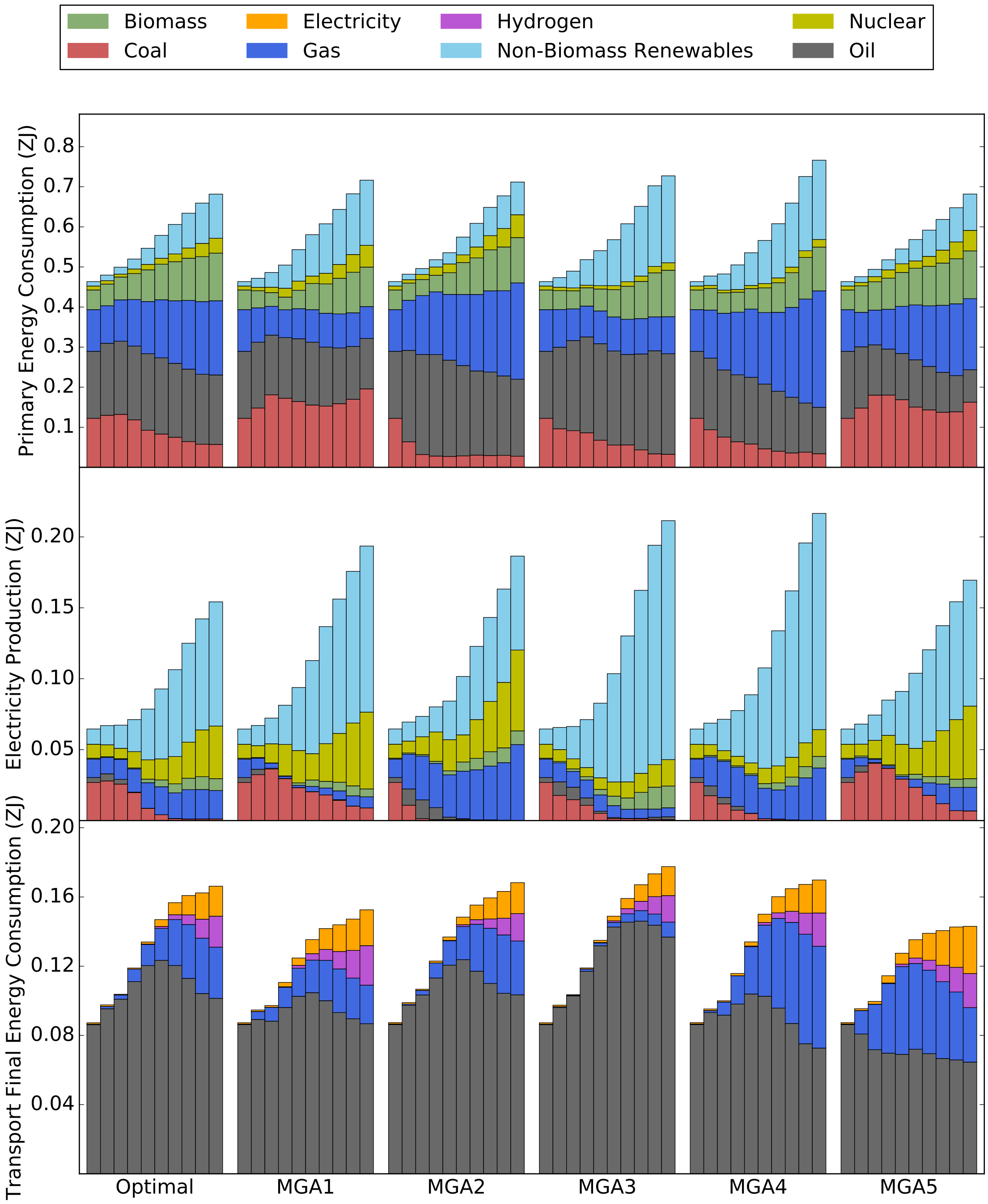

Figure 8: Plot showing how different components of the global energy system evolve between 2005-2050 in our mitigation scenario. The panels are the same as the left hand column of Fig. 2 but only for a slack of 5% and at 5 yearly steps rather than cumulative over the modelled period.

we've seen in the BAU scenario. We do note that this is the conclusion when difference on the level of primary energy is used to explore the space. It may well be that if a more elaborated objective function was used, one that would measure difference not only on the level of primary energy, but also in terms of, for example, sector specific final energy portfolios more room for variability would again exist. Unfortunately each new element in the objective function increases the computational burden significantly and this exercise is therefore left for a model that is more streamlined than our global integrated assessment model.

To show how the transition of the energy system proceeds in this scenario as a function of time, in Fig. 8 we plot the same three left hand panels as in Fig. 5 but this time at 5 yearly steps between 2010-2050 rather than cumulative totals over that period for the optimal and all five iterations at 5% slack. This chart demonstrates the growth of renewables in the power sector and the decline of oil use toward mid century in transport. It also demonstrates how differences between MGA iterations and the optimal run typically grow as one moves closer to 2050 and the model's flexibility increases. Thus, the differences between two iterations can be quite a bit more striking for 2050 than they are across the full time horizon.

In summary, the results presented in this section demonstrate how the MGA technique used here can assess the impact of structural uncertainty on key model output and establish whether consistent insights emerge. In particular, we find that transport continues to rely significantly on oil and renewables are a consistent feature in the electricity sector when emissions from the global energy system are constrained to follow a moderately aggressive decarbonisation pathway out to 2050. We have also found that the diversity of solutions in the near optimal space of our mitigation scenario is less than in the BAU case, the former being more constrained and thus having less flexibility to vary the primary resources used. We consider it to be of particular importance to communicate information emerging from an analysis like ours to policy makers. Firstly, it is key to highlight the elements of the energy system that do remain largely unchanged across the iterations and cost slacks, therefore suggesting more robust insights, and those that do not. Secondly, it is imperative to convey that there is likely to be a range of, possibly, significantly different trajectories that are nearly as good as the cost optimal solution, so that the transition suggested by the latter is not automatically seen as the only alternative for the future. Thirdly, to highlight structural uncertainty in general to those whose task it is to make robust decisions under uncertainty.

Comparison with Hop-Skip-Jump MGA

Within the literature, DeCarolis (2011) was the first to apply the concept of MGA to an energy system model and employed the so-called Hop-Skip-Jump (HSJ) technique (here after MGAHSJ), developed by E. Downey Brill et al. (1982) in the context of land use planning. In this section we compare our approach to that of the HSJ method, with a particular focus on how diverse the generated near-optimal solutions are.

The HSJ method follows the same first two steps as outlined previously, i.e. the model is run in standard formulation to find an optimal transition pathway and total system cost and this cost is then scaled up by some slack and entered into the model as a new constraint. The HSJ approach then uses a different third step which here we configure to function at the same primary energy carrier level as our technique and to use the normalised sector method of DeCarolis et al. (2015):

1. Record the amount of each primary energy carrier used in the optimal as a fraction of total primary energy consumption, e.g. coal use may account for 30% (0.3) of total primary energy while renewables may only be 5% (0.05).

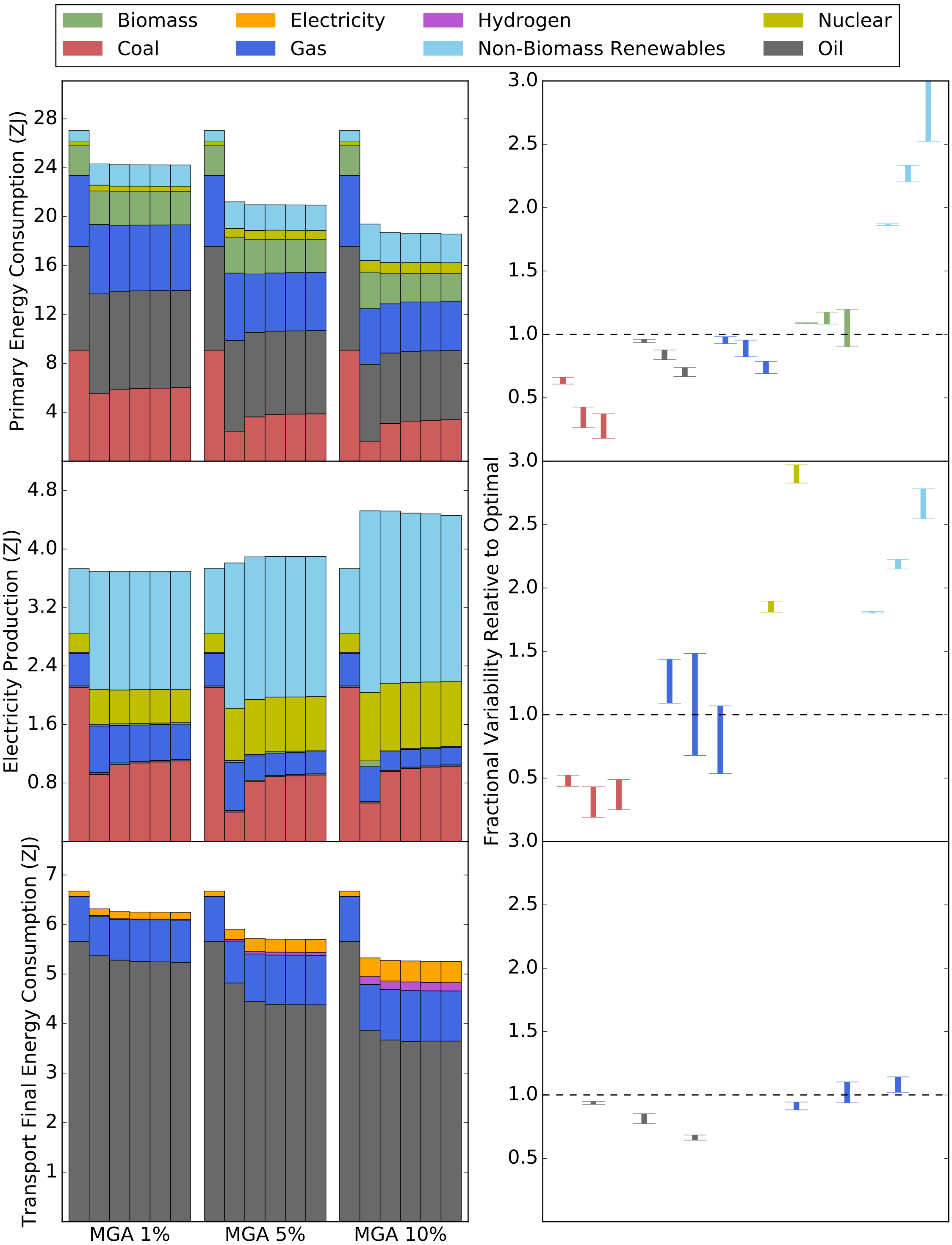

Figure 9: Plot showing cumulative primary energy consumption from our cost optimal BAU run and five HSJ MGA runs, left panel, and the fractional variability across the MGA iterations, right panel.

2. The new objective function then becomes:

$$Minimise \quad \sum_i PE\_frac\_optimal_i \times PE_i \tag{2}$$

$$\text{s.t. } tot\_sys\_cost \leq optimal\_sys\_cost \times (1 + slack)$$
$$slack \in 1\%,5\%,10\%$$

   where again i is the full set of primary energy carriers used in TIAM-UCL, PE is their cumulative consumption and $PE\_frac\_optimal_i$ is the variable obtained from step 1 and includes all energy carriers even if their fractional use is zero. After each iteration the latter variable is updated in a cumulative fashion, i.e. if the fraction of primary energy from coal in the optimal case was 0.3 and 0.2 in the first MGA iteration then its weight for the second iteration would be 0.5. In this way MGA seeks to find maximally different solutions in terms of their primary energy carrier mix by forcing out carriers that have featured strongly in the optimal and all previous iterations. Here we test HSJ MGA using our BAU scenario, as it leaves room for more flexibility than the mitigation scenario does.

In Fig. 9 we plot the results from MGAHSJ in the same format at Fig. 2, and so the figures are directly comparable (although the left panel y-axis scales are slightly different). From the former figure we see that the first MGAHSJ iteration is significantly different from the optimal across all sectors and slacks. However, subsequent iterations seem to be only slightly different and this can be verified by the right hand panels of Fig. 9, which shows little relative variability, at least compared to our MGA implementation, across the runs at each slack. Fig. 2 indicates that there is significant solution diversity in the near optimal space of this scenario and so it would seem, at least in this case, that MGAHSJ does not perform as well as the method applied here at finding a set of maximally different pathways. We speculate, that this is related to the relatively small number of decision variables (primary energy carriers) that can be brought into the solution and that almost all of these variables have non-zero values, and therefore non-zero fractional weight, beyond the first MGAHSJ iteration. In addition, we also note that MGAHSJ includes the level of primary energy use in the objective function and thus provides an incentive to minimize the use and, potentially, get stuck in that state. As such, we conclude that, at least when applied in this way, our MGA implementation is better able to generate maximally diverse near cost minimum solutions.

Conclusions

Long time horizon E3 models are an important resource for understanding the alternatives when seeking to mitigate global climate change while simultaneously addressing the rest of the so-called energy trilemma. In recent decades such models have been used extensively to map out possible energy system transition pathways that respond to this challenging problem and provide valuable insights to policy makers. However, given that their usage at the science-policy interface has become ubiquitous and that they are increasingly complex beasts, it is critical to assess and communicate how the significant uncertainties inherent to this type of modelling impact their output and to steer the discourse away from point results or precise looking, single trajectories.

It is worth noting that outside the global context, the technique described here could be applied to other cost optimising energy system models at the national and sub-national scales to help policy makers understand the ramifications of near-optimal solutions on their particular planning problem. For example, it could be directly applied to the UK TIMES whole energy system model (UKTM) also developed at the UCL Energy Institute. UKTM is the primary long term energy system planning model used by the UK government to understand how to respond to the country's ambitious climate policy which mandates an 80% reduction in greenhouse gas emissions relative to 1990 levels by 2050. Our version of MGA could be used to explore the near-optimal solution space of a scenario that meets this target and to identify consistent insights across those solutions as we have done here. Such information could provide decision makers with vital information about the elements of the energy system for which technological flexibility exists and about the ones that are more locked-in to a specific path, thus greatly helping the formulation of policies.

Broadly speaking, the output uncertainty budget of such models is driven by input parameter uncertainty, e.g. a lack of precise knowledge of future technology costs, resource potentials, etc, and structural uncertainty, i.e. the model does not capture the full complexity of the system it is trying to represent. Here we have described and demonstrated one technique to elucidate the impact of a portion of the total structural uncertainty budget of a global E3 model, TIAM-UCL, on the results it provides. To do this we relax the key structural assumption of cost optimality and then seek to explore the diversity of energy systems that exist within the model's near cost optimal solution space using a novel, at least to energy systems analysis, formulation of MGA. From this we can identify if any features of the proposed optimal transition pathway are robust to policy makers deviating from cost minimal decision making, in effect measuring the sensitivity of the results of the cost optimal solution. Turning that around, we are also able to demonstrate that relatively minor increases to total system cost can lead to significantly different transition pathways, thus suggesting that if non-cost related objectives are, in reality, also considered, the preferred trajectories could well look very different. From a methodological stand point, at a given slack, our approach in effect explores the multidimensional shape of the near cost optimal solution space in terms of whichever variables are in the MGA objective function and, therefore, provides an assessment of the scope of their variability in that region.

A summary of the key insights gained from applying our MGA implementation to two scenarios based on Shared Socio-economic Pathway 2, at three levels of permitted total system cost increase or slack, is as follows:

- Even at 1% slack, and therefore a particularly restricted near optimal space to search, we observe significant diversity/spread in the consumption of a number of important energy carriers at the primary energy level and, as a consequence, further into the energy system for our BAU scenario. This suggests that, in light of real world uncertainties and the multitude of non-cost related objectives, transitions very different from the cost optimal one can not be easily considered any "worse" or less plausible. The observed variability in the consumption of important energy carriers is seen to increase as the MGA total system cost constraint grows with increasing slack. Of particular note is the variability of coal and gas, which is largely driven by their substitutability in, for instance, electricity production. This interaction, together with increased renewable energy consumption and to a lesser extent fuel switching in the residential and commercial sectors, drives significant variation in CO_2 emissions relative to the optimal solution, which also tends to escalate with increasing slack. However, because the MGA formulation used here creates difference between the current iteration and all previous iterations plus the optimal in terms of primary energy consumption, in certain cases more slack does not always mean more variability on the sectoral level, e.g. gas use in transport or total energy system CO_2 emissions in 2050.

- The most consistent insight emerging from our BAU scenario is the continuing oil consumption, particularly that in the transport sector, and this remains unchanged even if total system cost is allowed to increase by 10%.

- With the addition of a global emissions pathway constraint, our mitigation scenario is typically seen to have less relative energy carrier consumption variability than the BAU scenario, while still also suggesting significantly different approaches to reducing emissions. At the primary energy level, coal is the most variable fuel with oil and biomass the most stable. Renewables are found to be a consistent feature of the global electricity system with the potential for their deployment seen to grow significantly as the MGA slack is increased. In a similar vein to the BAU scenario, oil remains the most important and stable fuel in the transport sector even at a permitted increase in total system cost of 10%.

- Furthermore, another key pair of insights from applying MGA to the mitigation scenario is the consistency with which, across all three slack levels tested here, the power sector is largely decarbonised by 2050 and that as the energy system transition proceeds, emissions are mitigated from the electricity sector before the transport sector.

- Finally, we have found that when HSJ MGA is applied in the same way as our MGA approach, i.e. at the primary energy level, it does not generate transition pathways that are as diverse as our implementation. This, we speculate, is because of how the formulation incentivises primary energy use reduction, combined with the limited number of decision variables used (10 energy carriers) and the fact that the majority of them become non-zero after the first iteration.

In closing, we reiterate that throughout this work we have explored only one aspect of TIAM-UCL's uncertainty budget and that it remains a task for a future study to fully understand the impact of structural and parametric uncertainty simultaneously within the framework of a global, whole energy system model.

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