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Actors behaving badly: Exploring the modelling of non-optimal behaviour in energy transitions

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ABSTRACT

There are real political and social barriers to climate mitigation that arise from multi-actor dynamics and micro-economic decisions. Exploratory analysis that captures key uncertainties in the energy system, including behaviour, is crucial for policy design aimed at achieving ambitious greenhouse gas (GHG) mitigation targets. This paper explores the case for developing policy assessments that include non-optimal behaviour in energy systems modelling. A stochastic system dynamic model of the energy system that features multiple actors with differentiated behaviours is used to investigate energy transition pathways that deviate from strict economic rationality. The results illustrate the risks of basing GHG reduction strategies on analysis that overlooks key insights into decision making from fields such as behavioural economics and political science.

1. Introduction

1.1. The case for exploratory analysis of climate mitigation policies

The 2015 Paris Agreement sets the stage for long term global reductions in greenhouse gas (GHG) emissions before the end of the century [1]. While there remain doubts over the cumulative level of ambition implied by current national pledges ([2] and [3]), the apportioning of the remaining global carbon budget [4], and whether or not a 1.5 °C or 2 °C stabilisation will be sufficient to avoid "dangerous" anthropogenic warming ([5] [6], and [7]), many nations are nevertheless striving to explore pathways to deep decarbonisation ([8] and [9]). The "ratchet" mechanism in the Paris Agreement that requires signatories to periodically update their pledges for GHG mitigation means that there is likely to continue to be a long term focus on energy systems analysis and energy transition pathways.

Quantitative formal models of energy systems play a central role in this endeavour by providing an exploratory framework for thinking about the future, and developing the evidence base for long term policy decisions [10]. Energy system models used for decarbonisation pathway analysis operate at multiple scales, with global models used for integrated assessment of climate impacts [11], national models used for exploring domestic trajectories towards low carbon futures [12], and sectoral models used to explore detailed technological transitions in key end-use sectors such as power, transport and buildings [13]. Reviews by Jebaraj and Iniyan [14], Bhattacharyya and Timilsina [15], and Pfenninger et al. [16] can give the reader an overview of many common types of energy models used in policy analysis.

When discussing the use of models for decision making, it is useful to reflect on the work of Börjeson et al. [17] who distinguish between *predictive*, *explorative* and *normative* analysis. The complexity of assessing long term (i.e. multi-decadal) transitions in energy systems precludes the use of quantitative models for *predictive (what will happen?)* purposes, especially given that future energy transitions are subject to conditions of *deep uncertainty* [18]. Energy systems models therefore tend to be used for either *normative* analysis, to determine how specific targets can be reached, or *explorative* analysis that aims to map out the landscape of plausible futures.

Deep decarbonisation analysis at the national scale (e.g. as demonstrated for countries such as the United States [19], the United Kingdom [20], or Portugal [21]) is likely to become a key focus for the modelling community in the future as individual countries review their Paris Agreement commitments. Quantitative analysis in support of strategic decarbonisation planning is carried out using a variety of techniques, with the classic distinction being between macroeconomically complete *top-down* models,

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technology rich *bottom-up* models, and *hybrids* (see Refs. [22] and [9]). Energy system optimisation models (ESOMs) are a popular class of bottom-up models that explore dynamic trade-offs between technology and resources. Examples of ESOMs in widespread use include OSeMOSYS [23], MARKAL [24], and TIMES [25]. Such models are often subject to several common critiques. Mathematically optimal solutions are often fragile to relatively small perturbations in the objective function, with the result that large changes in what could be interpreted as the "best" course of action can sometimes be found within a relatively small range of costs (see Refs. [26] and [27]). It has been suggested that over-reliance on cost-optimisation risks leading to overly deterministic analysis that investigates only a narrow range of possible futures [28], and that heavily constrained model runs might simply be reflecting the biases (conscious or otherwise) of the model operator [29]. It is also argued that ESOMs with perfect foresight can lead policymakers to under-estimate the challenge of using policy instruments to drive energy transitions, both because technology switching (if not constrained by other factors) occurs rapidly in the models and because costs are often the only modelled driver behind technology selection [30]. *Ex post* analysis of past scenario studies based on cost-optimisation analysis sometimes finds that nearly all real world developments have occurred outside of the previously modelled range of outcomes [31]. There is therefore a material requirement for new approaches to energy systems analysis that attempts a broader consideration of uncertainties [32].

The strong and active research community around energy systems modelling is making a number of parallel efforts to respond to these challenges. Modellers continue to develop techniques to expand the consideration of uncertainty in models. For example, approaches for understanding parametric uncertainties (e.g. by using Monte Carlo analysis [33]) and structural uncertainties (e.g. through implementing Modelling-to-Generate Alternatives approaches [34]) in models are becoming more widespread, as are multi-model comparison exercises [35]. Attempts to improve the representation of decision making include the development of myopic optimisation models [36] and models that employ stochastic programming and robust optimisation techniques [37]. Finally, there are efforts to improve the representation of actor behaviour in energy systems models. While it has long been typical practice to vary hurdle rates in ESOMs to explore time preference variation, models that account for a wider spectrum of behavioural parameters, such as heterogeneous choice behaviour, are becoming increasingly common [13].

1.2. Behavioural complexity in energy modelling

This paper focuses primarily on exploring the influence of non-optimal actor behaviour on long term decarbonisation pathways, as part of wider efforts to better address key uncertainties in energy systems analysis. That key stakeholders and individuals do not always exhibit purely cost optimising behaviour has been empirically observed for decades in energy policy. For example, rational economic analysis indicates that building energy efficiency measures are a "low hanging fruit" that should be rapidly adopted due to their cost-effective contribution to GHG mitigation, fuel poverty reduction, and energy security objectives. However, non-cost barriers to the widespread adoption of energy efficiency measures have historically prevented uptake to the levels expected by policymakers (e.g. Refs. [38] and [39]), in a phenomenon often termed "the energy efficiency gap" ([40] and [41]).

Failure or under-achievement in energy efficiency programmes is unfortunately common, with the collapse of the UK Government's flagship thermal improvement programme, the "Green Deal" being a recent prominent example [42]. During its short lifespan, the scheme achieved penetration rates far below anticipated levels and was abruptly cancelled with no replacement policy in place. A post-mortem report by the UK National Audit Office (NAO) linked the spectacular failure of the programme directly to poor policy design, which did not account for key behavioural factors in the consumer analysis and which ultimately "did not persuade householders that energy efficiency measures are worth paying for" [43].

Clearly, behavioural uncertainties cannot be safely ignored in policy design. Analysis shows that achieving deep decarbonisation is likely to require GHG reductions across the economy [8], including not only changes to energy generation but also in end-use demand sectors such as industry, buildings and transport. The level of agency that policymakers possess to influence transitions will vary by sector. In some countries, energy generation and other large industries may be state-owned or strongly regulated, giving the government powerful levers to direct investment in low carbon alternatives to fossil fuels. However, in all but the most repressive regimes, governments often have comparatively little influence over individual choices made by private citizens about what products they choose to purchase and use in their daily lives. This introduces significant uncertainties into decarbonisation pathways that are related to consumer behaviour in areas such as homes (e.g. building heating) and personal mobility (particularly road transport).

These uncertainties are often difficult to capture explicitly or remain underexplored in much energy systems analysis. It is typical for energy economy models to employ mathematical formulations based on cost optimisation, representing the allocation of resources on the basis of a single social planning agent who acts with perfect foresight. This omnipotent actor has no direct counterpart in reality, and acts as a representative proxy for high levels of collaboration, forward planning, and information exchange between different countries (at the global level) and economic sectors (at the national scale). This abstraction is not a barrier to the use of such tools for identifying cost-optimal pathways to normative futures, but does pose particular challenges when models are used in a more exploratory fashion to understand the range of possible futures that might transpire. For discussion purposes, we can further disaggregate behavioural uncertainties into:

i. The dynamics of decision making between actors and institutions, and;
ii. Micro-economic decision making by individual actors

1.2.1. Behavioural dynamics between actors and institutions

Historical analysis of past energy transitions shows that socio-technical change is often driven by politics and the power gradients between key stakeholders that supported different technologies or infrastructures. Useful examples can be found in a variety of sources, such as the work of Fouquet and Pearson [44], Sovacool [45], Fouquet [46], and Wilson and Grübler [47]. Historically, transformative changes in energy have only taken place relatively slowly, over multi-decade timescales [48], in contrast to the rapid transitions often observed in models. Real-world decision making occurs between multiple parties against a shifting set of political, economic and social priorities. This results in an environment where poorly coordinated policies, policies that directly oppose one another, or policies that are implemented in law but not enforced in practice can and do exist simultaneously. This leads to a policy environment that is sometimes characterised as being of a "second-best" nature ([49] and [50]), in contrast to the idealised "first-best" policymaking often found in models. Modellers themselves often acknowledge that the degree of coordination that needs to be