Why Rapid and Deep Decarbonization isn't Simple: Linking Bottom-up Socio-technical Decision-making Insights with Top-down Macroeconomic Analyses

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Abstract

Energy-economy-emissions modeling has commonly projected that the rapid and significant reductions in greenhouse gas emissions (GHGs) required to avoid the most significant consequences of climate change are, in theory, attainable with emissions policies and existing technologies. However, the assumptions of rates of change embodied in the technological deployments and retirements of these projections may not be consistent with existing socio-technical bottlenecks. This paper proposes to evaluate the top-down projections of a Computable General Equilibrium (CGE) model—one of a number of energy-economy-emissions modeling approaches commonly used for assessing the impacts of decarbonization—with a bottom-up framework representing the aggregated effect of project planning and approval processes. The Socio-technical Decision-making Model (SDM) will be used to construct an upper-bound achievability limit for project developments, given timelines and constraints for regulatory approval, capital investment cycles, public acceptance, and other socio-technical considerations. Results from this framework can be used to develop energy and climate change policy targets more cognizant of the sensitivity of predictions to highly uncertain social, economic, and technical outcomes and adaptations. Illustrative scenarios of nuclear power generation in the U.S. are presented to extend and improve our current understanding of CGE model predictions of technical feasibility, as well as the manner in which alternative parameterization for socioeconomic and political impediments can modify simulated pathways. A key finding is that the deployment of nuclear power technologies as a low-carbon generation resource in the U.S.

may need to be constrained below economic projections due to support from political, regulatory, industrial, and social drivers. Future research efforts will focus on employing expert elicitation techniques in order to characterize the current scientific range of beliefs regarding the SDM's parameters for targeted technological, sectoral, and regional evaluations.

1. Introduction

Rapid and significant reductions in greenhouse gas emissions (GHGs), the scale of which will likely be unprecedented, are widely believed to be necessary to meaningfully address climate change. Numerous energy-economy-emissions models have projected that the levels of GHG reductions required to avoid the most significant consequences of climate change are, in fact, attainable with the implementation of emissions policies (e.g. carbon taxing, cap and trade), existing technologies (e.g. renewable energy resources), and moderate investment costs [1]. Despite continued cost and efficiency improvements in the state-of-the-art of these solutions, the combined commitments embodied in the Paris Agreement fall far short of the levels required to prevent global temperature rises of more than 2ºC [2], even while international progress towards the decarbonization goals presented at the Paris Agreement remains slow [3]. There exists, therefore, a discrepancy between what is technically possible for global decarbonization and the constraints imposed by political, social, and economic factors that slow transition processes. These socio-technical factors and processes may have significant leverage in promoting or constraining inertia in a low-carbon transition [4]–[6]. Furthermore, the impact of critical bottlenecks on the pace of transition and the subsequent risk that delays could pose in meeting global emissions reduction targets may be mitigated if they can be identified in advance.

A rapid *socio-technical* transition to a low-carbon future will require the development and deployment of technical projects and infrastructure coupled with their effective integration within society. Some of the barriers to broadscale penetration of low-carbon energy involve technical and economic limitations, for example, the need for curtailment and storage for fluctuating wind and solar power [7], [8], and the need for new grid infrastructure to reliably transmit and regulate these resources [9], [10]. Other barriers are present primarily due to social, behavioral, and political factors that affect lifestyle, purchasing, production, marketing, and related choices made by individuals, households, communities, firms, and nations. While important strides have been made in recent years to better understand these factors, major challenges remain in assessing and predicting how human behavior will change under evolving social, economic, and environmental conditions [11]–[15]. Addressing the coevolution of social and technical elements in a low-carbon transition will thus require decision-making models that extend beyond techno-economic analysis and incorporate behavioral, social, political, and institutional dynamics, each of which may be subject to path dependencies [16], [17]. These transition barriers contribute to information lags, lack of investment capital for individuals and firms, and an unwillingness by consumers to change their energy sources, transmission modes, and usage patterns.

Quantitative modeling can offer the formal structure and explicit evidence necessary to inform policy processes for meaningfully addressing climate change. Efforts to reduce GHG emissions need to take into account both macro- and microeconomic effects, as well as the limits and possibilities of our current and future physical technologies. Computable General Equilibrium (CGE) models have been frequently applied to assess the response of national, regional, or global economies to changes in macroeconomic conditions, factor productivities, trade and taxation policy, and other demographic, technological, and economic factors. They offer a highly idealized and simplified representation of the real world [18], [19], yet are able to analyze the economic impacts of decarbonization strategies and estimate the behavior of economies globally in response to change [20]–[22].

CGE model simulations are not intended to provide precise predictions of economic outcomes multiple decades into the future. Except in a few cases, CGE models have not been sufficiently validated against past data to support such prediction, and available comparisons indicate an inconsistent range of performance for national- and technology-specific transitions [23]–[29]. Like the scenarios (or storylines) which help guide the selection of sets of inputs to CGE models, results are understood to provide only soft inferences over a broad range of plausible outcomes. The specification of ranges, error bars, probabilities, or other measures of uncertainty for energy model predictions has been increasingly recommended and implemented in scenario and model applications [30]–[34]. With the limited current fidelity of CGE and other long-term modeling approaches, these models may best be viewed as experimental microcosms, where the effects of model structure, inputs, and parameter values on system interactions and transition rates can be explored in a structured manner.

While many uncertainties and choices arise in the development and application of a CGE model, for instance, in the specification of regional and sectoral aggregation [35], [36], part of the failure to match previous changes may lie in the inability of these models to adequately represent critical socio-technical factors that present realistic influences on the rate of transition to new energy-economic systems [37], [38]. In this paper I take an initial step to providing methods that can be used to conduct experiments on the effects of including these factors.

To that end, I propose a framework to evaluate top-down macroeconomic projections of technological rates of change by linking a bottom-up representation of the aggregated effect of project planning and approval processes. The common quantitative foundation of these complementary methods will provide insights into the feasibility of decarbonization projections for specific technologies, sectors, and regions. The remainder of this paper is organized as follows: Section 2 discusses existing approaches to evaluating socio-technical transitions with numerical modeling techniques. Section 3 describes the rationale for CGE modeling and the choice of a CGE model. Section 4 introduces the framework of the bottom-up approach to socio-technical analysis. Section 5 illustrates the application of these combined methods by means of a scenario-based example. And Section 6 offers conclusions and planned research directions.

2. Existing approaches to evaluating socio-technical transitions with quantitative modeling

Progress in linking socio-technical transition analysis with energy-economy-emissions modeling has been limited by fundamental differences between these two disciplines. Although numerical (e.g. CGE) models offer analytical strengths for evaluating low-carbon transitions, they rely on a mathematical representation of the world distilled to a coarse level of simplification. Socio-technical dimensions have long been analyzed externally to formal models because factors like heterogenous actor preferences and the social, political, and cultural landscape reconfigurations that they involve are difficult to represent with mathematical equations. Yet these dimensions play a critical role in describing realistic pressures in societal transitions and are, therefore, major drivers of model uncertainty.

Recent methods for linking these two approaches include the development of the IPCC's Shared Socioeconomic Pathways and Representative Concentration Pathways [39], [40]; relying on historical technological growth dynamics to provide insight into modeling projections [41], [42]; constructing models with alternative assumptions and structures (e.g. agent-based models [43], [44], socio-technical energy transition models [45]); and establishing "dialogue" between model-based and narrative scenarios [46] and employing "bridging strategies" between the quantitative and socio-technical disciplines [47]–[49].

This work benefits from these efforts to introduce realism into a low-carbon transition assessment, and attempts to proceed further by analyzing the effects of socio-technical factors and processes in relation to rates of change and bottleneck development.

3. CGE modeling with BAEGEM

CGE models are a common tool for energy-economy-emissions analysis because of their top-down, macroeconomic approach to evaluating the impact of public policies and system externalities on all sectors of the economy. Importantly, the neoclassical foundation of these models provides a consistent framework for describing the exchange of money, goods, and services between economic agents and constructing macroeconomic indicators (e.g. GDP, government tax revenue and spending, savings and investment). Due to the need for striking a balance between model fidelity (i.e. maintaining macroeconomic and physical identities and balances) and computational tractability, the database of a CGE model is aggregated to some specified level of granularity (e.g. countries to regions).

Depending on the purpose of the analysis, CGE models can be static (i.e. simulation of a single time step) or dynamic (i.e. explicit representation of time-related adjustments to growth trajectories). This latter category of models is especially suitable for analyzing the impacts and dynamics of a transition. A CGE simulation typically begins with a state of equilibrium, followed by the introduction of an exogenous change, or "shock," to the economy. CGE models are useful in climate change impact evaluation because public policies designed to reduce GHG emissions (e.g. carbon taxing) or environmental consequences of climate change (e.g. reduced agricultural yields) can be modeled as shocks and their subsequent impacts can be quantified at all levels of the economy.

For this work, I have chosen to use BAEGEM, a recursively dynamic CGE model of the world economy developed by BAEconomics Propriety Limited [50]. For each time step, BAEGEM simulates the interrelationships between economic growth, international trade, resource constraints, production factors, GHG emissions, and climate change policies for a set of economic agents (i.e. households, firms, governments, investors, importers/exporters). A schematic diagram of BAEGEM's structure is provided in **Figure 1**. BAEGEM is based upon the approach of the Global Trade Analysis Project (GTAP) model [51]. GDP growth rate assumptions are based on International Monetary Fund and Global Insights projections, while population growth rates are based on the medium variant of the United Nations World Population Prospects. The model is simulated in this study with single-year time steps, covering the period from 2007 to 2060, using an 18 region, 26 production sector aggregation of the GTAP Version 8 database.

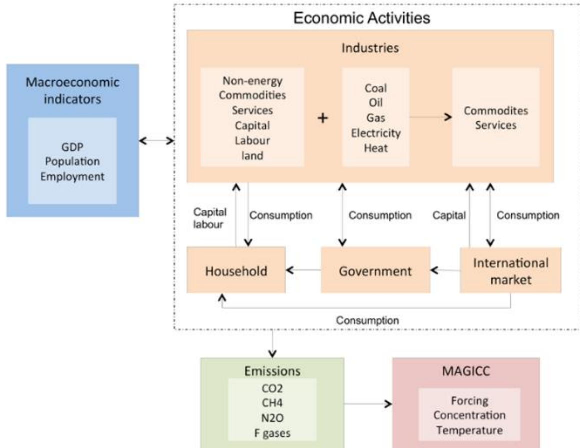

Figure 1: BAEGEM is a recursive dynamic CGE model and, additional to its core, includes government, energy, and GHG emissions modules [50].

BAEGEM offers distinct advantages over other models for this evaluation of climate-related policies because the core of the model is complemented by several interlinked satellite modules: (i) the government module; (ii) the energy module; and (iii) the GHG emissions module. The government module is used to represent government budget positions and the interactions with expenditure and tax revenue. The energy module tracks the production of primary and secondary energy and its consumption by governments, households, and firms. The GHG module tracks the emissions of Kyoto gases (i.e. CO_2, CH_4, N_2O, HFCs, PFCs, and SF_6) over their production, transformation, consumption, and combustion cycles. Furthermore, electricity supply from nine technologies (i.e. coal, oil, gas, nuclear, hydro, wind, solar, biomass, and other renewable resources) is modeled by means of a "technology bundle" approach. The bottom-up approach of technology bundles, which assumes that each generation technology produces the same finished product but uses a different mix of inputs, allows a better representation of technology-specific detail and the supply and demand implications for the economy.

BAEGEM provides a high degree of technological, sectoral, and regional detail to support an analysis of rate impacts in a low-carbon transition. The model is, however, subject to limits largely imposed by its neoclassical nature. Its equations assume that all actors are rational in their profit- or utility-maximizing decisions. Its aggregate orientation (e.g. representative regional household) does not offer insights into distributional effects and equity aspects of a global transition. And the model does not comprehensively represent carbon capture and sequestration (CCS) and other negative emissions technologies. Alternative approaches to overcoming these limitations fall into two categories: (a) make the model more complicated, or (b) minimize changes and complications to the model but deploy complementary approaches outside the model. The choice to pursue the latter option is further explored in the following sections.

4. Architecture of the Socio-technical Decision-making Model

I propose to evaluate the feasibility of technology projections with the development of a Socio-technical Decision-making Model (SDM) representing insights from assessments that consider greater end-user heterogeneity, realistic market behavior, and end-use technology details. The conceptual linkage between the CGE model and SDM is illustrated in **Figure 2**, in which the CGE projections for specific technologies will be assessed in the context of realistic societal processes embodied by the SDM.

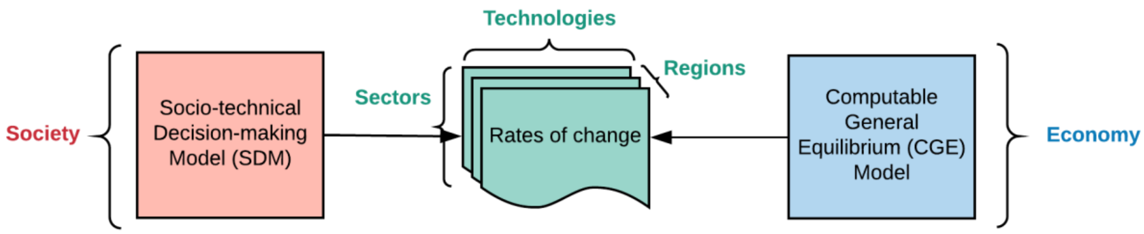

Figure 2: The linkage between bottom-up SDM formal and informal processes and top-down CGE modeling projections in evaluating technology- and region-specific rates of change can reveal modeling inconsistencies and realistic challenges.

For any given technical project of considerable scale, there exists a set of established steps and checkpoints, some more explicitly defined than others, that the project must satisfy before it can be commissioned and begin providing services for the economy. These socio-technical factors, which are not adequately captured by a CGE modeling framework, represent decision-making realities that can influence the project's deployment. Then, when aggregated to an economy-wide level, they have leverage to either constrain or accelerate the deployment trajectory of an entire technology. The SDM seeks to characterize these processes and their project- and economy-level impacts.

The first step of the SDM involves identifying a specific technology for a particular sector and region in order to deliver targeted insights. Next, participatory modeling or expert elicitation techniques can be used to synthesize the various socio-technical processes that govern a project's feasibility and rate of development. For instance, some of the characteristics which might affect the market uptake of mitigation technologies and socio-technical transitions include:

- Motivation and Key Drivers: The availability of resources and the performance of the proposed solution must be proven to a high-level of confidence with the project's investors.

A clear rationale for the project's construction and long-term operation, whether economic, political, or otherwise, should be defined.

- Acceptance: Public acceptance involves multi-dimensional, dynamic processes characterized at social, community, and market acceptance levels and can assert extraordinary influence on a project's development, installation, and use [52]. Acquiring a "social license to operate" and respectfully and honestly engaging with the public can serve to ensure the long-term viability of a project [53], [54].
- Regulations and Permitting: Environmental permits and resource license rights are often necessary for exploration and appraisal activities. An environmental assessment may be required by the regulator prior to a final investment decision (FID). For its operational phase, a project will need to secure additional permits and ensure its performance meets regulatory expectations, while closure of the project must comply with further requirements.
- Capital and Financing: Mobilizing the investment and financing for a project, specific to the project's scale and risk profile, requires careful coordination of capital resources. The decision-making processes of the investment, whether funded by the public and/or private sector, throughout the project's lifetime may be conceptualized as stage-gated, where each stage represents an investment decision that could result in a "stop, go, or recycle" decision [55, Ch. 3].
- Site Location and Operations: The project should be situated to efficiently take advantage of natural resources and any necessary distribution infrastructure. The project's technical and operational strategy should focus on maximizing performance while minimizing local negative externalities (e.g. erosion, ecological damage, industrial noise and lights).

Given project-specific characterizations, an upper-bound economic achievability limit can be approximated with an idealized S-shaped diffusion curve using the mathematical logistic function. By definition, any new technology begins with some pioneering projects and an initial low level of deployment. If successful, it proceeds to a high level of deployment, at which point it may experience saturation limits, which tend to slow the rate of deployment. In between, there is a growth stage characterized by a period with a maximum deployment rate. This process, which can be depicted by an S-curve, is commonly observed in mass consumer markets but can also be seen in industrial settings [56]**,** where new deployment is accelerated by positive network externalities provided by the growing in-place stock of previous adoptions [57].

The SDM S-curve seeks to represent the deployment of actual, physical projects that comprise the total installed capacity of a technology. **Equation 1** presents the logistic function, where $f(t)$ is the installed capacity or net generation at time t, L represents the saturation level, or the maximum level of deployment in the long term, k at the mid-point of the curve represents the industry's technical capacity, subject to socio-technical influences to deliver that operating capacity, and t_m represents the time to the inflection point where the maximum growth rate occurs.

$$f(t) = \frac{L}{1 + e^{-k(t-t_m)}} \tag{1}$$

When the SDM is overlaid with a CGE projection, this approach can categorize modeling values as unrealistic due to socio-technical influences (red zone), or as feasible, and potentially able to be accelerated, due to enabling factors (blue zone), as illustrated in **Figure 3.** The insights obtained from this approach could be used to apply exogenous inputs to the CGE model, refine or calibrate the CGE parameters, identify key socio-technical "pinch points," and quantify emission reduction opportunities. The identification and quantification of rate-limiting factors, as well as initiating factors, catalyzing factors, and factors affecting saturation levels, provide a new framework and basis for analysis of bottleneck-relieving strategies.

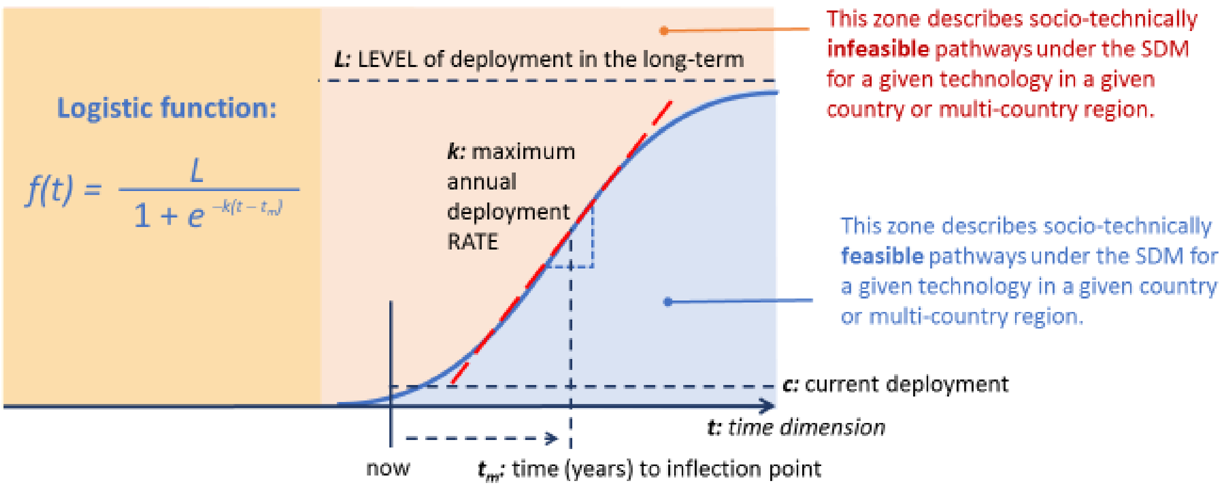

Figure 3: The S-curve, as constructed by the logistic function, can identify socio-technically feasible and infeasible pathways when overlaid with CGE modeling projections.

As described in the following application, the utility of the SDM's methodology depends upon:

i. The provision of a rational basis for selecting the base-case model parameters for different future socioeconomic, energy, and climate conditions;

ii. The application of extensive sensitivity analysis to explore how model predictions change as model input parameters vary/covary; and

iii. Interaction with experts to elicit their scientific beliefs and with stakeholders to understand their outcomes of greatest concern in order to determine whether they are sufficiently informed by the model framework and able to provide input that expresses their knowledge and preferences.

5. Illustrative application of the linked SDM-CGE approach: U.S. nuclear power scenarios

i. Background and scenario introduction

An assessment of 2018 GHG emissions contributions represented in BAEGEM's database established that a few key countries and sectors disproportionately produce the majority of global emissions.[1] Therefore, to illustrate the capacity of the SDM for evaluating projections of significant GHG emissions contributions, I will focus on assessing the role of a specific technology—nuclear power—in achieving decarbonization goals for one of the world's largest CO_2 emitters, the U.S.[2] Realizing a worldwide low-carbon transition critically depends on decarbonizing the U.S. electricity sector.

In this section, four scenarios of nuclear power projections in the U.S., as summarized in **Table 1**, are introduced and their implications are assessed in terms of GHG contributions and reductions. In the base case, BAEGEM identifies the economically optimal long-term mix of electricity generation in the U.S. without policy intervention. Then, in the policy scenario, an annually increasing carbon tax is implemented and the optimal mix of generation resources subsequently adjusts to this policy intervention. S-curves constructed with the SDM then suggest that socio-technical factors could constrain the deployment of nuclear power technologies. Exogenous inputs are implemented in the model to adjust the projections of nuclear power's growth accordingly. This analysis illustrates the ability of the SDM to review macroeconomic projections and enable alternative pathways for meeting climate targets.

[1] 15% of the countries (i.e. China, the U.S., E.U. members, India) represented in the model's regional aggregation contributed 59% of 2018 global GHG emissions (refer to **Figure A1** in **Appendix S1**). Similarly, from a sectoral perspective, 25% of the sectors in the model's sectoral aggregation contributed 76% of 2018 industrial emissions (refer to **Figure A2** in **Appendix S2**).

[2] The global electricity sector contributed 33% of 2018 sectoral emissions, while the U.S. contributed 14% of 2018 regional emissions.

Table 1: Four scenarios are presented to assess nuclear power projections and associated GHG emissions in the U.S. with and without carbon taxes.

Scenario	Description
Base case	Baseline evolution.
Policy	Carbon tax shocks ($5/ton/year from 2018 - 2060), aligned with progressive climate targets.
Modified base case	Baseline evolution is constrained by average value of expert-assessed upper limit to nuclear penetration.
Modified policy	Policy case (including carbon tax shocks) is constrained by average value of expert-assessed upper limit to nuclear penetration.

ii. Base case scenario: Economics drive the solution

A reference (i.e. business-as-usual) scenario is constructed for BAEGEM in which the world's economies are simulated without any exogenous shocks and GHG emissions are allowed to develop in the absence of any climate mitigation policies. **Figure 4** presents the model's forecast of the electricity generation mix in the U.S. until 2060, based on macroeconomic interactions and assumptions of population and GDP growth rates. Coal and natural gas, supplemented by smaller contributions from nuclear and renewables, largely drive the future of generation in the U.S. Total annual electricity generation is projected to reach 7,800 TWh by 2060, of which nuclear power is expected to contribute 950 TWh, or approximately a 12% share of the total generation.

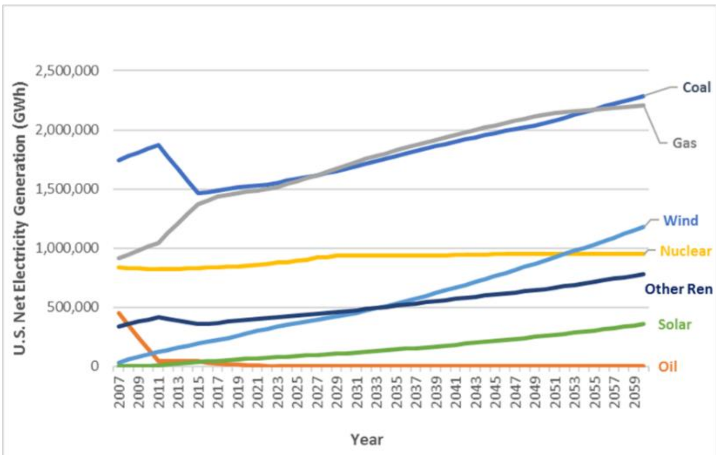

Figure 4: Scenario A1 presents the economically optimal long-term mix of electricity generation in the U.S. without policy intervention. Nuclear power in the U.S. provides 12% of total electricity generation by 2060.

Socio-technical factors can be expected to govern the achievability of the technological projections set forth by the model in this scenario. A key question to answer, then, is determining whether the macroeconomic and microeconomic factors accounted for by the CGE model represent the entirety of realistic influences, or would other socio-technical factors that are not represented within the CGE model influence the technology's projection?

iii. Policy scenario: Implementing a carbon tax

The effectiveness of a carbon tax policy in adjusting the U.S. electricity generation portfolio to reduce GHG emissions is assessed in this scenario. An economic shock is simulated in which a global CO_2 tax of $5/ton is implemented in 2018, rising by $5/ton each year to $215/ton by 2060.[3] **Figure 5** illustrates the effect of this tax on the U.S. electricity generation mix, in which the total annual electricity generation is projected to be slightly higher by 2060 (i.e. 8,200 TWh) because of demand effects resulting from the policy. Nuclear generation again contributes 950 TWh, or approximately 12% of the total mix, by 2060, but coal is largely substituted out in favor of wind, solar, and other renewable energy technologies. Although analyzing the feasibility of such a high penetration of renewable energy resources is external to the scope of this work, the cost advantage for renewable energy resources would be very high, as demonstrated here in the case of the U.S., if such a policy could be agreed upon and implemented.

[3] The realistic difficulties of implementing a universal carbon tax of such a magnitude are understood. The purpose of the carbon tax in this scenario is intended to be illustrative. Indeed, delays in implementing the tax or limitations in its rate could be modeled as a social-regulatory impedance.

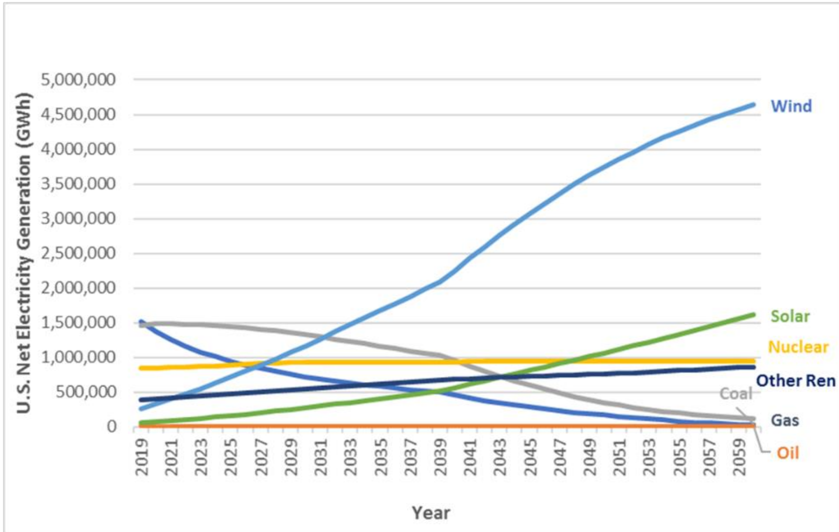

Figure 5: The policy scenario implements a global CO_2 tax beginning in 2018. Nuclear power in the U.S. provides 12% of total electricity generation by 2060, while coal generation is largely substituted out in favor of renewable energy resources.

iv. Reviewing projections in the context of socio-technical factors

I next evaluate the nuclear power projections of the base and policy scenarios based on measures of political, regulatory, industrial, and social capacities. As a proof-of-concept of the bottom-up approach of the SDM, I reference analyses by Morgan et al. on the future of nuclear power in the U.S. [58] and Ford et al. on employing expert elicitation to review U.S. nuclear power projections [59]. Morgan et al. contend that "it is most unlikely that nuclear power will be able to contribute to decarbonization in the United States" primarily because the existing U.S. nuclear fleet is shrinking, advanced designs aren't immediately available, and the promise of small modular reactors is fading. Furthermore, Ford et al. asked nuclear experts to forecast the percentage of electricity that U.S. nuclear power will generate in the near (2030) and medium (2060) terms under both status quo and aggressive growth assumptions [8].[4]

[4] For comparison purposes, I assume that the experts' "status quo" assumptions are equivalent to my base scenario, while the "aggressive growth" assumptions are similar in magnitude to the ratcheting CO_2 tax implemented in the policy scenario.

Using the results from the expert elicitation process by Ford et al., I construct a set of S-curves with the logistic function in order to simulate average, pessimistic, and optimistic projections of nuclear power's potential deployment in the U.S. for the base and policy scenarios and to represent the range of uncertainty inherent in these projections. **Figures 6 and 7** present depictions of the S-curve estimates in comparison to the nuclear power projection of the BAEGEM scenarios as a percentage of total system generation. **Figure 6** illustrates the nuclear experts' status quo estimates versus the BAEGEM base scenario projections, while **Figure 7** illustrates the nuclear experts' aggressive growth estimates versus the BAEGEM policy scenario projections.

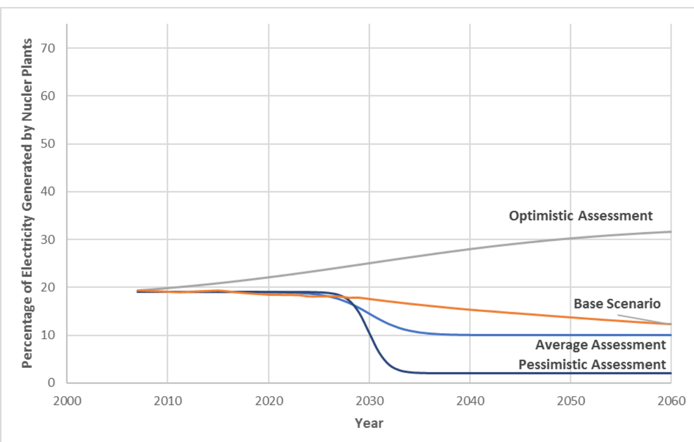

Figure 6: Comparison between the nuclear power projection of the CGE base scenario and the status quo S-curve estimates demonstrates that BAEGEM assumes a higher level of nuclear power saturation into the future than the average and pessimistic assessments.

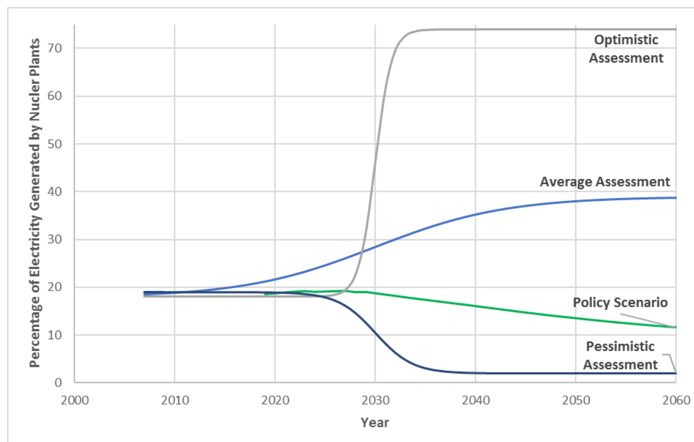

Figure 7: Comparison between the nuclear power projection of the CGE policy scenario and the aggressive growth S-curve estimates demonstrates that BAEGEM assumes a higher level of nuclear power saturation than only the pessimistic assessment.

Expert assessment of nuclear power's role in meeting U.S. climate targets concludes that the technology likely cannot be deployed to as great an extent as expressed by the BAEGEM base scenario. The SDM would characterize the CGE projection in this base case as socio-technically infeasible because the CGE values lie above all but the optimistic expert assessment

S-curves. However, in the policy scenario with an aggressive global CO_2 tax implemented, the BAEGEM nuclear projections are likely socio-technically feasible because the CGE projection lies below both the optimistic and average expert assessment values.

vi. Scenario synthesis

Although nuclear power's potential to make significant contributions to a low-carbon future is generally acknowledged [60], the technology's ability to realize mitigation achievements is dependent upon socio-technical, region-specific enabling factors [58], [59], [61], [62]. The long-term electricity generation portfolio of each of the scenarios presented in this section varies depending on the existence of carbon taxing and socio-technical factors. The introduction of the carbon tax in the policy scenario shifted the bulk of the generation mix to renewable resources.

In addition to impacting the system generation mix, the various inputs and shocks of each of the scenarios have implications for national GHG emissions. To illustrate how BAEGEM's projections can be aligned with the S-curve estimates derived from the Ford et al. analysis, BAEGEM's rate and saturation parameters are exogenously constrained to accept no more than the percentage of nuclear power penetration allowed by the experts' average status quo estimates.

Figure 8 demonstrates the GHG emissions profile of each scenario until 2060, in which a "modified" scenario refers to implementing expert constraints on the extent of allowable nuclear penetration. In the base case, the implementation of the model's exogenous inputs aligned with constraining socio-technical factors results in an approximately 3.3% increase in CO_2 emissions (i.e. additional 1.35 GtC) from 2007 – 2060 in the Modified Base scenario compared to the original base scenario; these additional emissions could be explained by substitution by cheap coal and gas for nuclear generation. In the policy case, the Modified Policy scenario results in an approximately 1.4% increase in CO_2 emissions from 2018 – 2060 than the original Policy scenario because of an increased share of generation by solar power and other renewable energy technologies. Therefore, implementing a carbon tax at a global or multi-regional scale as well as incentivizing key energy technologies (e.g. nuclear power) with emissions policies or other mechanisms has the potential to deliver significant GHG emissions reductions.

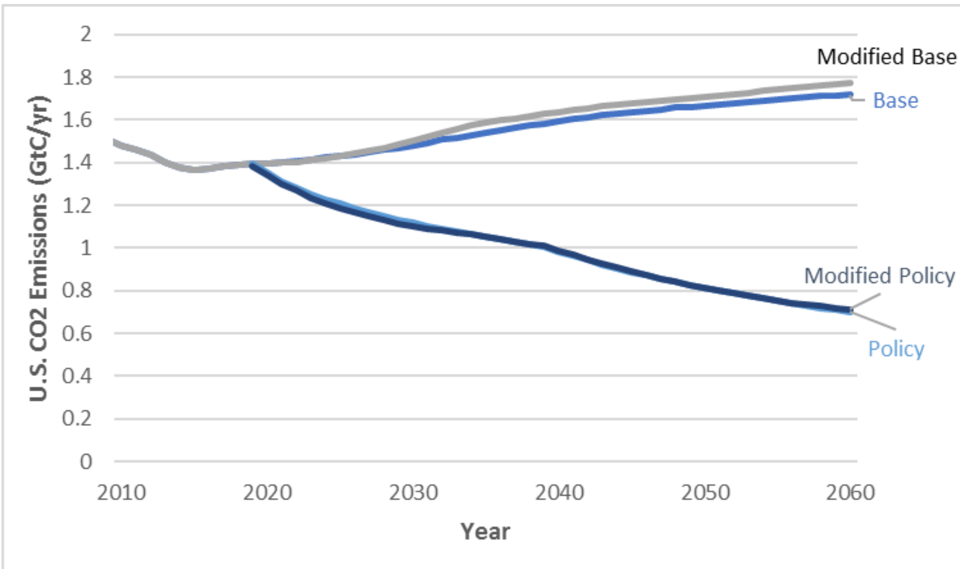

Figure 8: Comparison of the GHG emissions of each of the modeled scenarios until 2060 illustrates that carbon taxing and exogenous socio-technical-driven inputs can alter emissions trajectories.

6. Conclusions and future direction

A rapid and deep decarbonization of the global economy is complicated by the constraints of technological systems and the socio-technical intersections into which they must fit. In fact, the IPCC Working Group III [39, Ch. 6] described the feasibility of decarbonization pathways as, "In many circumstances, there are clear physical constraints that can render particular long-term goals physically impossible. However, in many cases, statements about feasibility are bound up in subjective assessments of the degree to which other characteristics of particular transformation pathways might influence the ability or desire of human societies to follow them."

Despite the urgency of global emission reduction targets, the achievable rates of change of decarbonization solutions and the rate-limiting bottlenecks they might encounter in meeting the targets remains largely unknown. The SDM-CGE framework proposed in this paper is able to assess the extent to which these "other characteristics" might influence the feasibility of technological projections. Taken independently, the two approaches may fail to consider some of the critical dynamics in an analysis of a rapid and deep decarbonization. However, the combination of the two approaches is able to more fully address key political, economic, social, technical, regulatory, and environmental factors.

After having described the design of the SDM-CGE approach and illustrated its usefulness by means of an application, my future efforts may be focused on applying this methodology to a broader set of case studies of established technologies that have yet to be deployed to a level necessary for a low carbon-transition (e.g. wind power, solar PV technology, CCS), examined in regions with significant GHG emissions (e.g. China, the U.S., the E.U., India). Experts familiar with the project development of a specific technology of interest will be interviewed to provide characterizations of individual projects for particular regions. Expert elicitation will be used in two stages of the SDM to represent the range of system assumptions: (1) to provide a characterization of a typical project's expected timeline and rate-limiting factors; and (2) to assess the accuracy and measures of uncertainty of the S-curve once constructed at the economy-wide level. Initial scoping of the planned expert elicitation effort is provided in

Appendix S2.

Understanding achievable rates of system transitions is fundamental to developing meaningful energy and climate change policy. The approach of top-down macroeconomic modeling coupled with bottom-up realistic, process-driven insights provides a testbed for exploring how low-carbon transitions could evolve. Robust and adaptive policies can then be developed to target specific technologies and address the underlying mechanisms of system transitions. In summary, this paper asserts that quantitative modeling of energy and economic systems can be supported by insights into real-world processes and socio-technical influences in order to support decarbonization efforts.

Acknowledgements

The author gratefully acknowledges the guidance provided by his advisors—Mitchell Small, Stephen Wilson, and Gabrielle Wong-Parodi—and additional support from Chris Greig, Joe Lane, and Gabriel Rioseco. This work was funded by the Dow Centre for Sustainable Engineering Innovation at the University of Queensland and the Department of Engineering and Public Policy at Carnegie Mellon University.

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Supplementary Information for Why Rapid and Deep Decarbonization isn't Simple

Appendix S1: Regional and sectoral GHG emissions contributions

An assessment of the significant GHG emissions contributions represented in BAEGEM's database for the year 2018 are presented for regions in **Figure A1** and sectors in **Figure A2**. 15% of the countries (i.e. China, the U.S., the E.U., and India) represented in the model's regional aggregation contribute 60% of global GHG emissions. And 25% of the model's aggregated sectors contribute 76% of industrial GHG emissions. Therefore, public policies and mitigation efforts should largely focus on addressing these key emissions contributors.

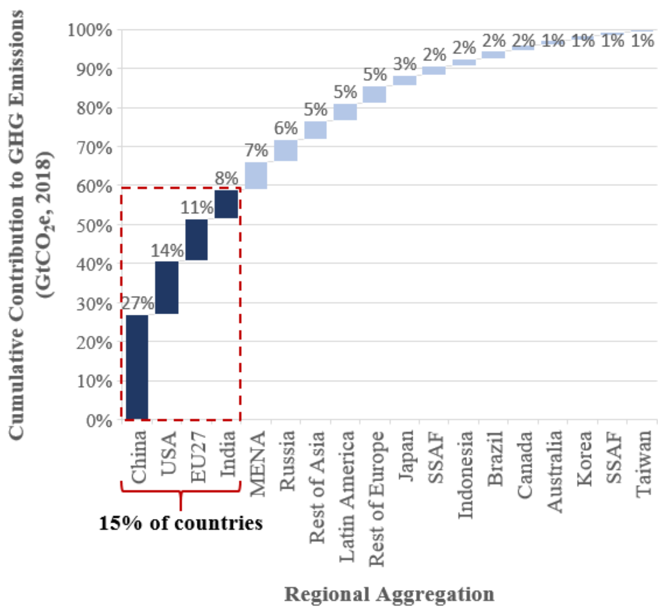

Figure A1: 15% of the countries in BAEGEM's regional aggregation contributed 59% of GHG emissions in 2018.

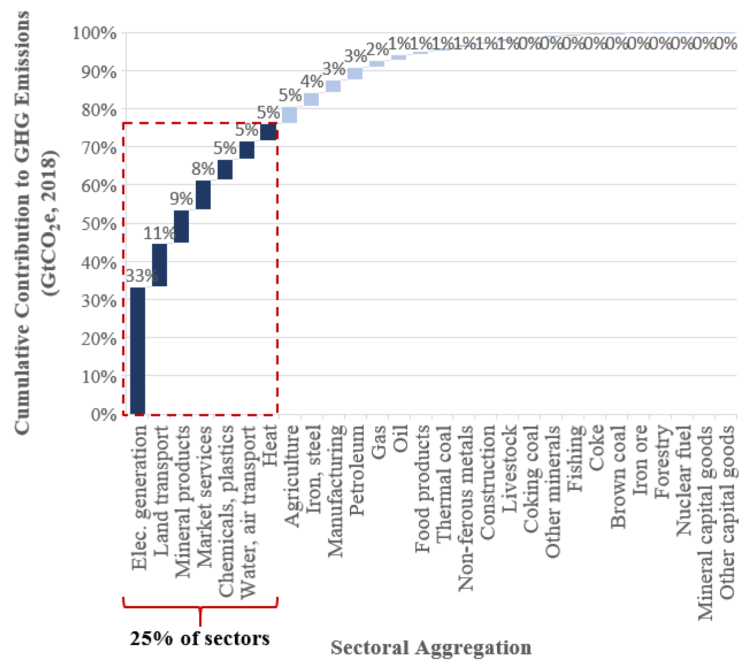

Figure A2: 25% of the sectors in BAEGEM's sectoral aggregation contributed 76% of industrial GHG emissions in 2018.

Appendix S2: Initial scoping of the planned expert elicitation effort

For each case analysis of a particular technology and region, we will aim to recruit approximately a dozen experts familiar with the technology from a combination of project development companies, regulatory agencies, financial institutions, and public planning departments. Then, an expert elicitation process will be conducted in two separate stages in order to identify and refine parameters and measures of uncertainty for the SDM:

In the first stage, we will rely on the expertise of the project's investigators to create an expert model of a technology's general development based on the "mental models" approach [63]. The expert model will seek to characterize and provide values for parameters related to anticipated project development timelines and bottlenecks as well as project cycle times, project sizes over time, and parallel project development for specific technologies and regions. Then, following the approach proposed by Rao et al. [64], we will ask each expert to comment on the appropriateness of the values selected for these parameters, and to provide replacements if the values offered are not found suitable. The objective of this step is to gain an understanding of the range of expert judgments and beliefs for the technology's future.

Next, the experts' judgements will be used to calculate an estimate of the technology's deployment at an economy-wide level, represented by an S-curve. If the various experts produce diverse estimates for a technology's expected deployment, it may not make sense to simply combine the judgements; rather, a distribution of the responses can be illustrated next to the mean approximation of the S-curve in order to capture the extent of the uncertainty and variability. Then, the S-curve projection will be presented to the experts for their open-ended assessment of its accuracy and representation of the technology's influencing factors. It may be necessary to conduct iterations of this approach until an adequate S-curve can be constructed for each technology and region of interest.