Exploring a Simulation Model of Canadian Energy Policy

Jason R. Wang, Patrick Steinmann

Prepared for the Canadian Energy Modelling Initiative

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by

Jason R. Wang[1], Patrick Steinmann[2]

[1] Independent Researcher, Edmonton, Alberta, Canada. Email: contact@jrwang.ca

[2] Independent Researcher, Wageningen, The Netherlands. Email: mail@patricksteinmann.com

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Abstract

We systematically explore the behavior of an integrated energy-climate-economy simulation model to determine the importance of factors behind reducing greenhouse gas emissions, and policy alternatives for reaching specific climate goals. We study the model's behavior across 184 input parameters and nine outcomes of interest using global sensitivity analysis and scenario discovery. For scenario discovery, we consider a climate-based and a policy threshold of success: 152 MtCO2e emissions per year by 2050, a representation of the Canadian Long Term Strategy, and net cumulative costs that are free or save money. We identify that a substantial industrial carbon tax of at least \$270 CAD/tCO2e is unavoidable, additional transmission capacity development not exceed 115% of no interventions, and building insulation capital costs improve by at least 19%. Our work highlights how the systematic exploration of complex simulation models can expose their underlying dynamics and constraints while reducing analyst bias and properly treating uncertainty, highlighting the importance for the modelling community to shift to an exploratory modelling paradigm.

Résumé

Nous explorons systématiquement le comportement d'un modèle de simulation intégré énergie-climat-économie afin de déterminer l'importance des facteurs à l'origine de la réduction des émissions de gaz à effet de serre, et les solutions de rechange pour atteindre des objectifs climatiques spécifiques. Nous étudions le comportement du modèle à travers 184 paramètres d'entrée et 34 résultats d'intérêt en utilisant l'analyse de sensibilité globale et la découverte de scénarios. Pour la découverte de scénarios, nous considérons un seuil de réussite basé sur le climat et un seuil politique : 152 MtCO2e d'émissions par an d'ici 2050, une représentation de la stratégie canadienne à long terme, et des coûts cumulatifs nets qui sont gratuits ou permettent de réaliser des économies. Nous déterminons qu'une taxe industrielle substantielle sur le carbone d'au moins 270 $ CAD/tCO2e est inévitable, que le développement de la capacité de transmission supplémentaire ne dépasse pas 115% de l'absence d'interventions et que les coûts d'investissement en isolation des bâtiments s'améliorent d'au moins 19%. Notre travail souligne comment l'exploration systématique de modèles de simulation complexes peut exposer leurs dynamiques et contraintes sous-jacentes tout en réduisant le biais des analystes et en traitant correctement l'incertitude, soulignant l'importance pour la communauté de la modélisation de passer à un paradigme de modélisation exploratoire.

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1. Introduction

Traditional modelling for policy support suffers from three key limitations: 1) stakeholders disagree over assumptions, structure, and measurable outcomes, 2) gaps in understanding between model builders, policy-makers, and the public over how modelling (and its conclusions) should be used, and 3) neglect for the modellers' biases in defining future scenarios *a priori* (Shortridge and Zaitchik, 2018). Together, these limitations are known within the literature as "Deep Uncertainty" (Lempert, Popper, and Bankes, 2003). This project applies techniques from Deep Uncertainty to analyze the Canada Energy Policy Simulator model, developed by the Pembina Institute and Energy Innovations, to show trade-offs between possible policy scenarios to reach the targets set out in Canada's November 2016 Long Term Strategy submission to the UNFCCC (Environment and Climate Change Canada, 2016), and how policy-relevant scenarios can be developed without modeller biases. The process would demonstrate how shifting where scenarios are defined to be analyzed and communicated can bridge gaps between stakeholders, modellers, and policy-makers. Finally, these approaches can also demonstrate how robust policies can be made.

The usefulness of models in policy support is not their complexity, but how they are analyzed and used. Weaver et al. (2013) argue that modellers' fixation over increasing resolution and complexity is a major limitation in energy and climate models' usefulness and persuasiveness in a policy context. And where models have been used to craft policies, they provide a snapshot of insights to craft static policies (Righetti et al., 2017). Despite the best efforts of model builders, and against their own knowledge, more time is usually spent on building models than exploring them for insights (Munson, 2012). Yet, complex models are not necessarily more useful. Yue et al. (2018) note in their review of energy system optimization models that most insufficiently or inadequately handle uncertainties, which limits analytical insight, lacks robustness, and may mislead decision-makers.

Furthermore, model scenarios are commonly misused, especially within the climate science and policy domain (Pielke and Ritchie, 2020). When model builders simplify their analysis to a small set of scenarios, which often includes a "reference" or "business-as-usual" scenario, they implicitly associate a higher likelihood to those scenarios occurring (Shortridge and Zaitchik, 2018), even if they disclaim that these are only possible states of the world. Assessing a limited set of scenarios also disposes consideration of other combinations of assumptions that may unexpectedly reach the same policy target (Lamontagne et al., 2018), leaving the policy support incomplete.

Parametric and structural uncertainties of elements of energy transition models often reflect conservative and static outlooks based on modellers' contemporary understanding of the world. Within the energy modelling space, the pace of technology deployment and price forecasts for solar photovoltaic installations and batteries, among other technologies, are commonly underestimated (Jaxa-Rozen and Trutnevyte, 2021; Evans, 2019; Phadke et al., 2021) and bias policy-makers towards less aggressive policy approaches. Modellers and policy-makers alike end up with a lagging perception of the world that requires frequent and iterative updates to reflect the rapid advancement in energy technologies, which can be cost-prohibitive and harms the reputation of modelling in general (Bankes, 1993). Similarly, traditional modelling approaches will adjust model structures and parameters and calibrate models until outcomes may fit within an accepted range, but the complexity and non-linearity of models limits modellers from drawing such causal inferences. Many sets of inputs can lead to the same outcomes (Oreskes, Shrader-Frechette, and Belitz, 1994).

Deep Uncertainty approaches address these model-use limitations and provide a pathway for modellers to more comprehensively analyze their models. One core Deep Uncertainty method, exploratory modelling, is an approach to use models by exploring complex and non-linear behaviour within models across many uncertainties (Bankes, 1993). Using an exploratory modelling approach in energy policy modelling allows for further opportunities in policy analysis, such as evaluating policy robustness and formulating adaptive policies, which is also known as Robust Decision-Making (RDM) (Lempert et al., 2006). It also communicates trade-offs between options more transparently. Lempert, Popper, and Bankes (2003), Shortridge and Zaitchik (2018), Weaver et al. (2013), and Steinmann et al. (2020) and Murphy et al. (2004) argue that modelling for policy analysis must use Deep Uncertainty approaches like exploratory modelling and Robust Decision-Making to both epistemologically incorporate uncertainties and leave the aforementioned policy modelling trap. While many existing energy system models avoid exploratory approaches, we demonstrate how these methods can be applied to Canadian energy policy, with both policy-related and scientific benefits.

2. Methods

2.1. The Model

In this analysis, we study the *Energy Policy Simulator* (EPS; also known as *Energy Policy Solutions*), designed by Energy Innovation. The model is free and open-source, and adapted for many jurisdictions around the world, covering 55% of global greenhouse gas (GHG) emissions. Its insights have been used in government assessments, policy research from environmental policy organizations, and in peer-reviewed works (e.g. Gallagher et al. (2019), Tian et al. (2019)).

The model takes an integrated assessment of various sectors as depicted in Figure 1. Notably, energy production is not not explicitly tracked, only through supply and demand. Therefore, policies that limit oil production are calculated exogenously and then integrated into the model.

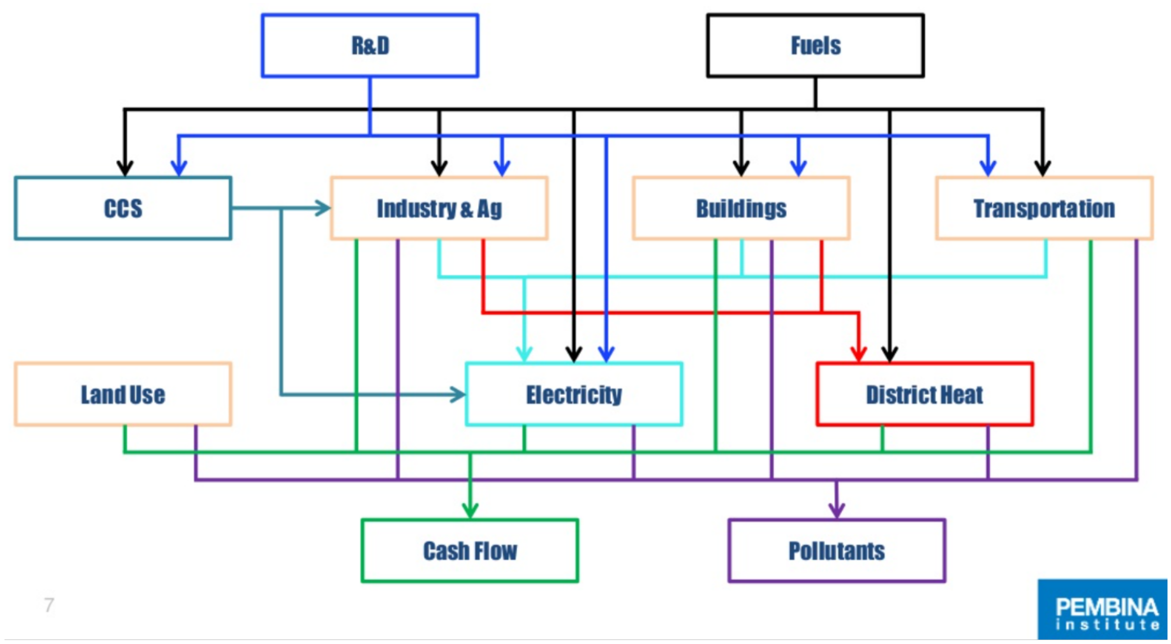


Figure 1: Stylized Structure of Energy Policy Simulator Model Structure

The model is developed in Vensim, a program for System Dynamics models. Data is entered into the model directly or through Excel and CSV files. Relationships between variables are defined through a combination of standard and differential equations.

Model and Data Source

In particular, we used the most recent branch of EPS adapted for Canada by Energy Innovation and the Pembina Institute in 2018 and 2019 v1.4.3. EPS exists as both an interactive webpage[1] and as a Vensim model[2]. The data input to the model are from publicly available government sources and from early 2016. Where Canadian data was unavailable, US data was used in lieu (Pembina Institute, 2019).

Model Parameters

The EPS model includes many parameters. The ones chosen for our study are the ones are the same as the 184 inputs and 34 outcomes on the online version of the model (listed in Section A.2) except the boolean for a 100 MtCO2e/year emissions cap on oil sands in Alberta. Most policy parameters are defined as a variable within the model, but the oil sands emission limit is implemented in the "policy implementation schedule" function of EPS. We were unable to replicate the web model's boolean control for the cap without modifying the model files; modifying, verifying, and validating structural changes to the model was out of the scope of this project. This choice is discussed further in paragraph 4.2.3.

We also include a comparison to the parameters chosen by the winner of the Pembina Institute's Youth Policy Design Competition (YPDC) (Urban, 2019), who did not enact the oil sands limit. The Pembina Institute ran a policy design competition in 2019[3], asking youth to use the model to design policies that meet Canada's GHG targets at minimal economic and political cost. The top three submissions' reports were published online.

Within Vensim, we used the model integration parameters set by Pembina Institute and Energy Innovation, notably, a one year time step and Euler integration method.

[1] https://canada.energypolicy.solutions/scenarios/home
[2] https://canada.energypolicy.solutions/docs/
[3] https://www.pembina.org/media-release/student-leaders-design-canadas-climate-and-energy-future

2.2. Exploratory Modelling and Scenarios

As described in the introduction, exploratory modelling is critical to providing policy analysis in a deeply uncertain world (Steinmann et al., 2020). Specifically, we use the Exploratory Modelling and Analysis (EMA) Workbench (Kwakkel, 2017)[4] as a hypervisor that drives multiple instances of Vensim and implement the various parameters sampled. The Workbench allows us to vary all model parameters at will, and study the effects on model outcomes. We ran all experiments using an 8-core AMD EPYC virtual machine with 20 GB of RAM on Google Cloud Platform.

Global Sensitivity Analysis

To understand the most influential parameters in the EPS, we perform global sensitivity analysis using the Sobol' (sic) method (Sobol', 1990) and Saltelli parameter sampling (Saltelli, 2004). Using global sensitivity analysis is preferable to local sensitivity analysis as it captures interactions between parameters, and cover the entire uncertainty space (Saltelli et al., 2019). Our analysis utilizes the SALib package (Herman and Usher, 2017) implemented in the EMA Workbench. We generated 374,000 simulation runs. We performed the analysis across the extended parameter ranges described in Section A.2, but also validated the results by re-running the analysis across the original parameter ranges defined by the Pembina Institute (extracted from the EPS website). Of the 34 available outcomes, we found nine that were of particular policy interest:

1. Cumulative CO2 emissions between 2017 and 2050
2. CO2 emissions in 2050
3. Change consumer cash flow
4. Change government cash flow
5. Change in industry cash flow
6. Lives saved
7. Change in outlays (total costs) across all sectors

[4] https://github.com/quaquel/EMAworkbench/

8. Change in outlays (total costs) across all sectors, assuming revenue neutral carbon tax
9. Other social benefits

Scenario Discovery

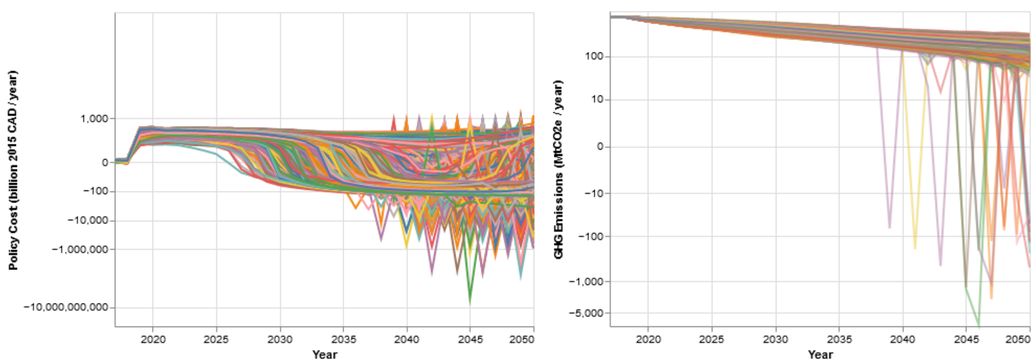
Conventional scenario-based planning approaches first define scenarios of interest, and then apply these to a simulation model, with the intent to compare the outcomes. Scenario discovery (Bryant and Lempert, 2010) shifts the creation of scenarios from what the analyst deems as likely or representative archetypes to an output of model analysis. A large sample of parametric configurations is simulated, and then the parameter ranges which generate outcomes of interest are identified using classification and induction algorithms. Scenario discovery differs from sensitivity analysis by looking through model outputs for interesting inputs rather than adjusting inputs to determine their impacts.

Scenario discovery requires defining a success condition against which every model run can be evaluated. In our case, we used an 80% reduction in GHG emissions relative to 2005 by 2050, which is the target in Canada's November 2016 Long Term Strategy submission (Environment and Climate Change Canada, 2016), as the primary metric. Based on the Pembina Institute's work, this is represented by an emission level of 152 MtCO2e/yr (Pembina Institute, 2019). We also look for policy packages that cumulatively cost nothing or save money in terms of total outlays, which includes capital, fuel, and operations and maintenance costs, as well as subsidies and taxes. While any set of criteria can be run, we chose these for simplicity to analyze and communicate. Then, we specified 600,000 experiments using Latin Hypercube sampling for the parameters, which samples each member of the parametric set at least once across all the scenarios and is more representative of a population than Monte Carlo sampling (McKay, Beckman, and Conover, 1979). The experiments took a total of 15 hours to complete. Next, we used the Patient Rule Induction Method (PRIM), a rule induction machine learning algorithm (Friedman and Fisher, 1999), to identify subspaces of the input parameters that would lead to policy success.

3. Results

3.1. Integration Errors

While conducting our model exploration, we discovered numerical integration errors in EPS for certain combinations of policy levers. We used spike detection routines to remove runs with integration errors from the data set for scenario discovery. Out of a set of 600,000 runs, 55,139 (9.0%) runs had integration errors, leaving 544,861 remaining runs. For global sensitivity analysis, a highly specific sampling scheme was used to reduce the number of required simulation runs, barring the removal of individual runs with integration errors. Instead, we conducted the global sensitivity analysis at an earlier time step ($t = 2027$) in the model runs, at which integration errors were not yet present.



(a) GHG

(b) Costs

Figure 2: Errors found in scenario discovery output data using spike detection. These runs were excluded from further analysis.

3.2. Global Sensitivity Analysis

In Figure 3, we plot the first-order effects S1 for the most influential model inputs (based on total-order effects, where ST $>$ 0.05) for a variety of model outputs of interest. A number of interesting patterns are apparent. *Carbon Tax [industry sector]* is the dominant input parameter, affecting nearly all outputs of interest to some degree, and being the only parameter of relevance for what are arguably the most important outputs (cumulative and final annual GHG emissions) in the context of long-term climate policy. It also appears as a relevant parameter for a number of outputs which are not traditionally associated with the effects of a carbon tax, such as social benefits. Conversely, *Carbon Tax [transportation sector]* is virtually irrelevant, impacting only government cash flow.

Further points of interest are that a subsidy on light electric vehicles seems to be primarily a method of transferring money from government to citizens, with no tangible climate effect. Additionally, subsidizing biomass negatively impacts mortality through increased harmful particulate emissions. For a full overview of these sensitivities and their confidence intervals, see Section A.3.

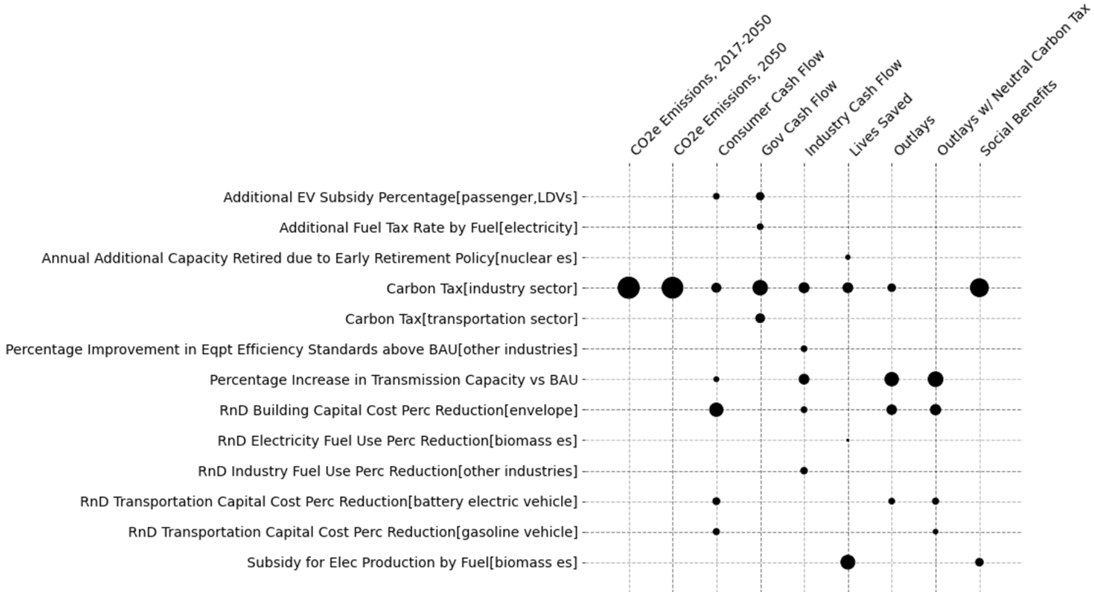


Figure 3: Sensitivities of model outputs (top) to inputs (left). Only the most sensitive (total order effect ST $>$ 0.05) inputs are shown. Dot size represents first order effect S1.

We additionally examined the global sensitivity analysis results by specific outcome, where we could also discern the relationship between the inputs. That is to say, since the global approach varies parameters simultaneously, this approach shows the collective influence of parameter combinations. For GHG emissions (Figure 4), we found that the *Carbon Tax [industry sector]* has a significantly influence than the next two most influential parameters, achieving afforestation and reforestation and capturing fugitive methane emissions. The latter two had a larger impact when used together than with the carbon tax. When viewing costs (Figure 5), we found transmission capacity and building insulation costs to be strongly linked. Both gasoline and battery electric vehicles were strongly linked, though the analysis does not show the direction of the link.

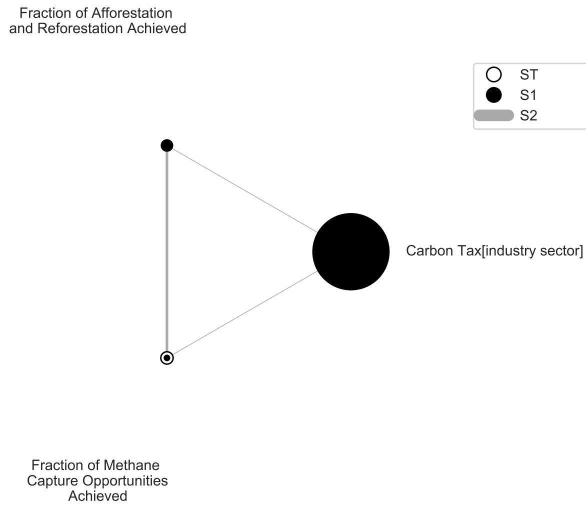


Figure 4: First, second, and total order sensitivities for most influential input parameters for outcome *Output Total CO2e Emissions*, with an inclusion threshold of ST > 0.02 due to the dominance of *Carbon Tax [industry sector]*. At a threshold this low, stochastic effects may dominate the true sensitivities.

3.3. Scenario Discovery

Our sampled results yielded a range of runs with a minimum of 32 and 403 MtCO2e emissions in 2050 and the total cumulative costs until 2050 ranges from -4249–5747 billion 2015 CAD (depicted in Figure 6). The winner of the Pembina Institute Youth Policy Design Competition (Urban, 2019) created a policy package by changing 58 policies from their default parameters, but it did not perform as well as the average of our set in 2050 GHG emissions, but was slightly cheaper than our results (see Figure 6c).

Using the PRIM algorithm, we found three restricted dimensions: 1) carbon tax in industry ($272.05–800 CAD), 2) increase in electricity transmission capacity (0–115%), and 3) reduction in building envelope capital costs (19–100%). The distribution of successful cases within these ranges is important to understand if these restricted ranges are useful and are depicted in

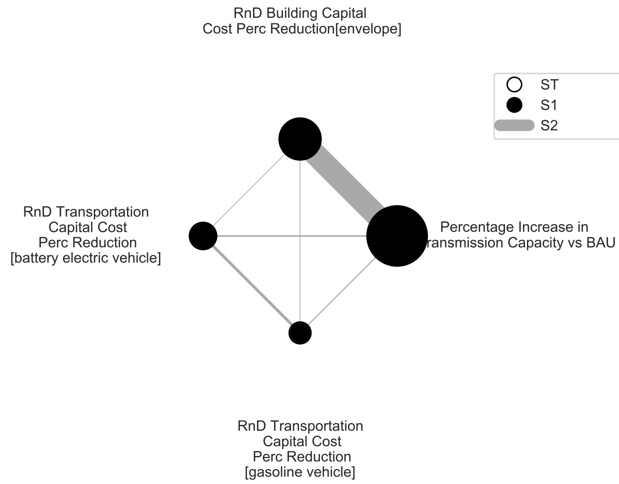


Figure 5: First, second, and total order sensitivities for most influential input parameters for outcome *Output Total Change in Outlays with Revenue Neutral Carbon Tax*, with an inclusion threshold of ST > 0.05. The influence of transmission capacity is apparent, along with its joint effect with reduced construction costs.

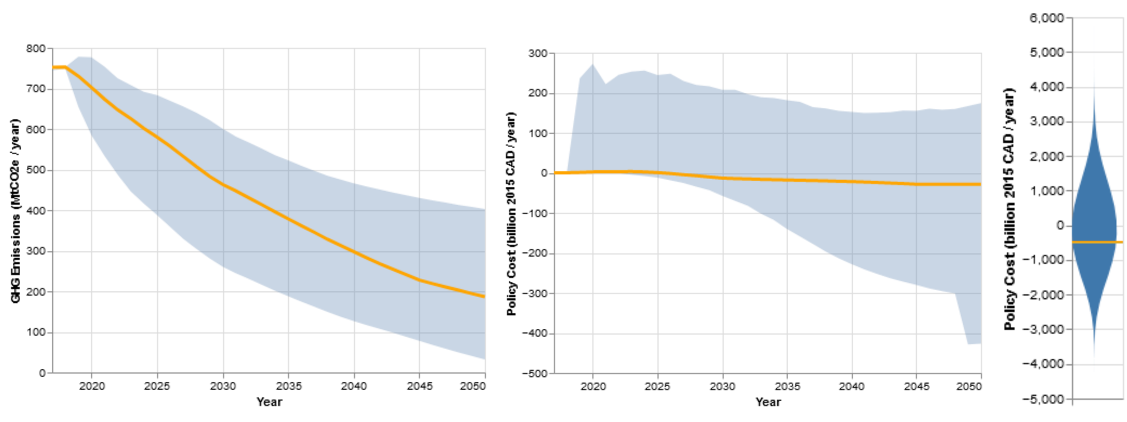


Figure 6: Min-max ranges of scenario discovery sampled runs (blue) compared to Youth Policy Design Contest winner (orange). (a) GHG emissions per year (b) Policy cost per year (c) Cumulative policy cost until 2050. Roughly half or more of our runs outperform the Youth Policy Design Contest winner's outputs.

Figure 7). None of the results show robust conclusions, but there are strong patterns. A high industrial carbon can still fail almost as often as it succeeds, but the lower the transmission capacity increase, the better the outcomes. Below around a 50% increase, more cases succeed than fail (the volume of successful runs noticeably exceeds failed runs). The more the capital costs of building envelopes, or building insulation, reduce, the higher the chance of success, though it never becomes more likely than failure.

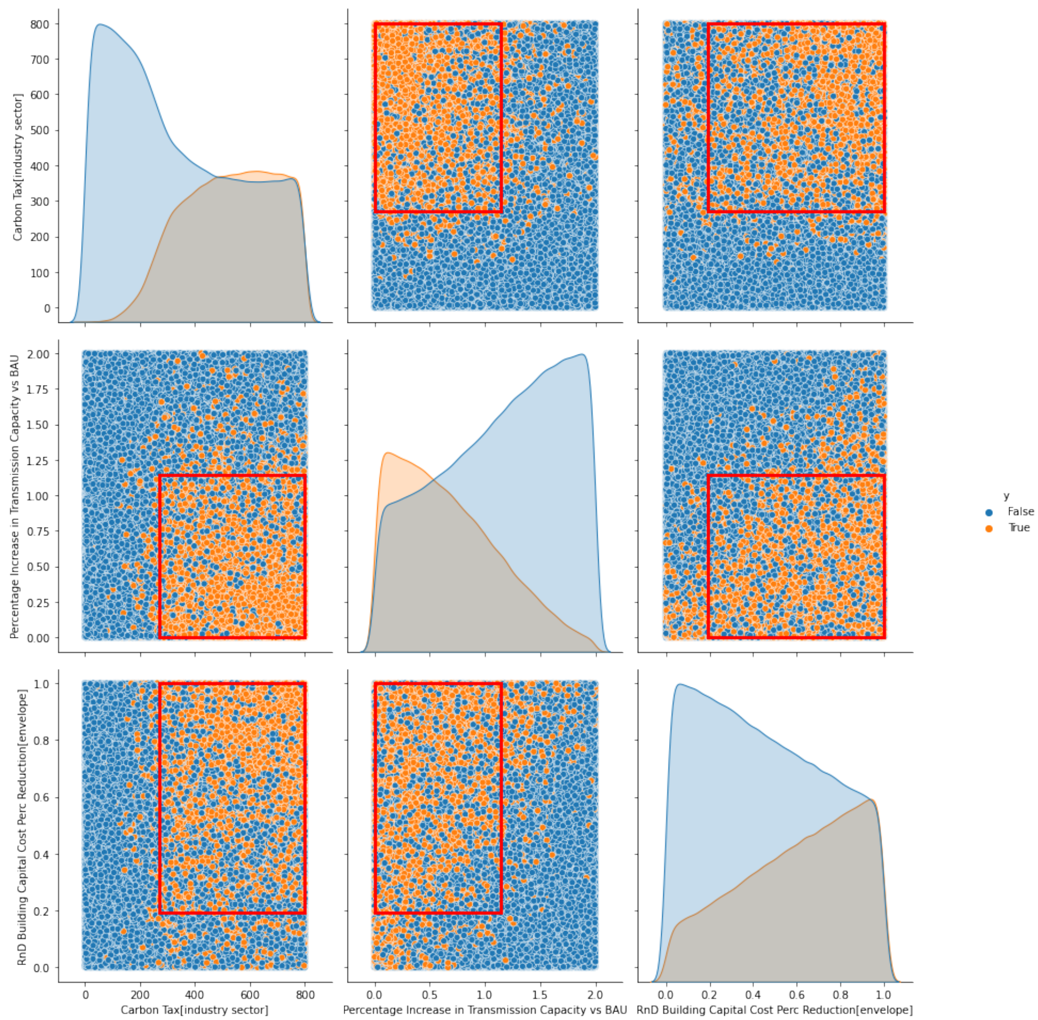


Figure 7: Pairplot of restricted dimensions in first GHG emissions subspace identified by PRIM. The density plots show the distribution of successful and failed runs for each parameter at its range of sampled values. The red box in the scatter plots shows the subspace for the dimension on the x axis.

PRIM can be prone to randomness. To test the robustness of these results, Bryant and Lempert (2010) proposed the resampling and quasi p-value tests. Resampling performs PRIM repeatedly and determines if the coverage and density values can be reproduced. Resampling 10 times gave 100% reproducibility in results. The quasi p-value (qp) is based on a null hypothesis that each parameter's range was found out of pure chance. In all three restricted dimensions, the ranges were defined with a qp of less than 0.0001. In all these cases, the null hypothesis could be rejected.

4. Discussion

4.1. Interpretation and Validity of Results

The high degree of overlap between the influential parameters identified independently by global sensitivity analysis and scenario discovery indicates our analytical results are robust and valid. In both cases, we found the same three parameters to be important to reducing GHGs and minimizing costs: industrial carbon tax, transmission capacity, and the capital cost of building insulation. Compared to common GHG abatement cost analyses, these are intuitive. Energy efficiency is the cheapest form of GHG reductions with negative abatement costs, and building heating represents large portions of energy demand. Increasing electricity capacity while electrifying is useful, but if done more than needed, capital costs begin to outweigh induced benefits. Carbon tax is widely seen as the most economically-efficient approach to reduce GHGs (Howard and Sylvan, 2015; Climate Leadership Council, 2019), and this model reinforces that view (or vice versa).

While the relationships between parameters found by global sensitivity analysis are interesting, they are more useful for understanding the complex energy system, as represented by the model, rather than answering specific policy questions. In this case, the link between battery and gasoline vehicles (Figure 5) probably indicates that 1) the transportation sector has a large cost impact and 2) consumers respond strongly to the costs of vehicles. The relationship between methane capture and afforestation and reforestation is likely because a strong industrial carbon tax reduces the need for their implementation, but without the tax, the two should be deployed together.

The scenario discovery results did not illuminate specific policy ranges that would generate a high confidence for success in both reducing emissions and being either free or cost-saving policy packages, at best showing ranges where success could be slightly on-par with failure. To be clear, this means that if just these three parameters were fixed within some range, there would be around a 50% chance of reaching the specific policy target regardless of what all other 181 parameter values are, and none of the others had a strong influence on the outcomes.

That the global sensitivity analysis results were themselves validated by repeating the analysis across a different set of input parameter ranges (as described in Section 2.2.1), with broadly similar outcomes. We also scenario discovery with cases where policies caused more harm to lives than doing nothing to understand the utility of the scenario discovery approach.

Focus on Carbon Tax

Through both global sensitivity analysis and scenario discovery, we identified carbon tax on industry as the most important parameter in the EPS. However, this parameter is so influential that it raises questions about the model's structure and behavior. As Mercure et al. (2019) showed, the underlying economic assumptions within integrated models, especially surrounding how innovation is funded, can lead to massively different analytical results. In EPS's case, the structure of cash flow between government, industry, and consumers could fundamentally leave industry more vulnerable to policy levers. In other words, the assumptions that define economic interactions in EPS could be why model outputs are so sensitive to the industrial carbon tax. Furthermore, carbon pricing policy has considered impacts to trade exposure, or competitiveness, of industrial carbon pricing and granted free allowances. However, this model does not include trade dynamics, which potentially leaves the pricing lever more effective than it would be in the real world.

Additionally, industrial behaviours are better understood than consumer and government ones. They are also easier to aggregate and represent mathematically. In the EPS (see Figure Figure 1), business relationships are explicitly defined, whereas social and political aspects that consumers and governments are more exposed to are less represented, if at all. This may bias model outcomes against what is easily represented. Finally, some critical aspects of industry are not captured at all, such as employment, again introducing a potential bias to measurable outcomes.

Validation through Scenario Discovery on Lives Lost

In our exploration, we discovered models runs where the number of lives saved became negative. To understand the driving factors behind this undesirable outcome and to validate the scenario discovery approach on related policy question, we also applied scenario discovery to cases where lives saved were negative at any point in the time series. These results were resampled 10 times and had 100% reproducibility. We found that the electricity production subsidy for biomass needed to be above 18%, new natural gas non-peaker power plants need to be banned, at least 5.1 GW of nuclear but less than 8096 MW hard coal-based electricity generators need to additionally shut down per year. These ranges and the distribution of cases are depicted in Figure 8. None of the conclusions are strong, but these important parameters make intuitive sense: weak policies to replace coal-fired electricity generation and strong support to implement biomass fuels leads to even more particulate pollution than doing nothing.

4.2. Usability for Policy Design

Exploratory Modelling Adds Value

Exploratory modelling added value to this analysis in two main ways: 1) we discovered the most important policies and ranges for these policies to meet the policy target and 2) we discovered model outcomes and behaviours that we probably would not have otherwise, or at least without spending much time within the model.

Global sensitivity analysis quantified how dominant the industrial carbon tax is and the irrelevance of other parameters. Combined with scenario discovery, we can confidently conclude – based on the model's interpretation of the world – that policy decisions are only important for a small subset of policies. Government funded innovation should focus more on just building insulation and not any other sector. Compared to the real world where analytical resources are stretched between many policy fields, our results advocate for a significantly more lean approach. Similarly, our analytical approach automates policy design through a systematic approach. Whereas the YPDC winner highlighted how policy is often made by incrementally adjusting levers – while simultaneously assessing factors like political feasibility and technological probability, which could bias modeller – scenario discovery narrows the

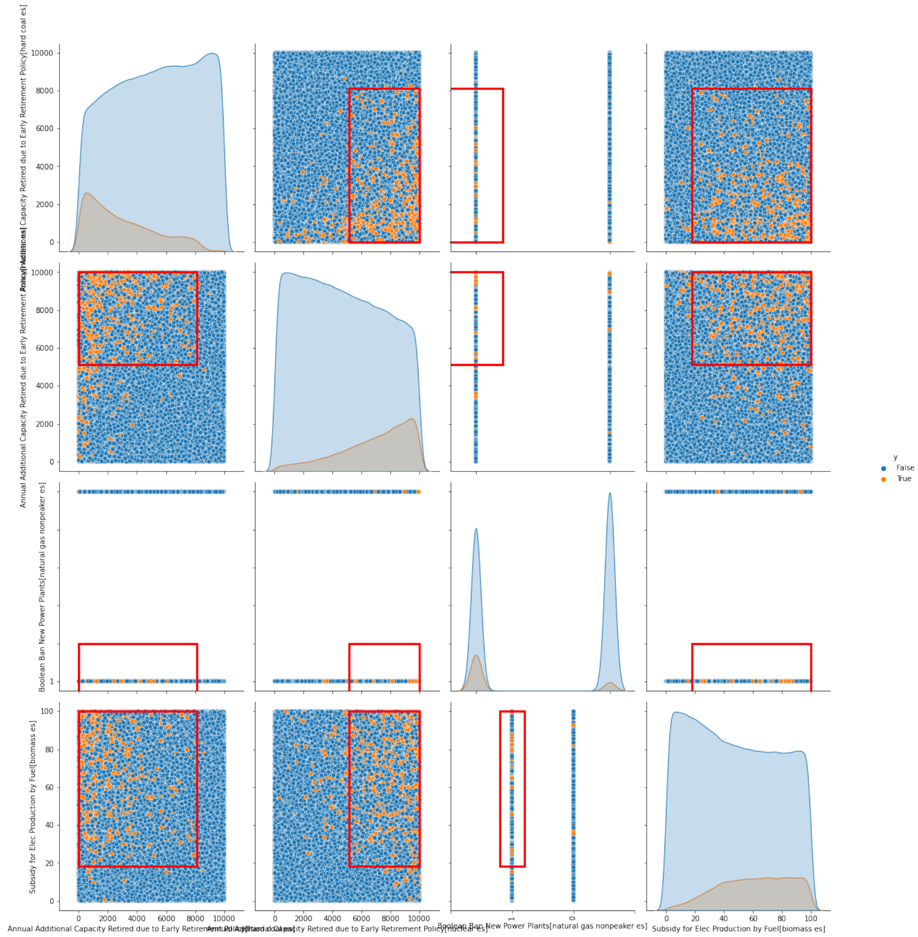


Figure 8: Pairplot of restricted dimensions for cases where lives are lost. Policies that slow down the phase-out of coal-fired electricity production and promote biomass use for electricity leads to more deaths, most likely due to additional particulate pollution.

scope of analysis and shifts the consideration of additional factors to later step. For example, if modellers and forecasters had sought to discover how a wide range of battery costs can or cannot meet policy outcomes, they would not have to react to the recent report that battery costs are already as low as others predicted would only occur beyond 2040 (Phadke et al., 2021). Scenario discovery would have saved modellers time in their minute adjustments-analysis cycle and in reassessing recommendations because a policy parameter is no longer valid.

Exploratory modelling also illuminated the many cases with integration errors. When models are built and validated for specific scenarios or purposes, they may make assumptions that could become internally inconsistent and yield a model unstable outside of those specific cases. We showed how running many scenarios, performing global rather than local sensitivity analysis, and scenario discovery can be used to reveal and debug special cases. Rule induction is particularly useful here because it could theoretically show that model errors can come from different regions of the input space. Without considering parameters together or a wide range of scenarios that are less influenced by modeller biases, analysts would be significantly more vulnerable to the nonuniqueness and overfitting problems that jeopardize the crediblity of their conclusions (Oreskes, Shrader-Frechette, and Belitz, 1994).

Fast Models are Better than Slow Models

As exploratory modelling requires many model runs to gather actionable insights, so models with fast run times are preferable. These models are often simpler, tending towards uncertainty rather than complexity – a trade-off that needs to be well-exposed for scientific and policy purposes (Helgeson et al., 2020; Spiegelhalter and Riesch, 2011). However, when assessing topics such as climate risks, addressing uncertainty is critical, especially because the parameters and structures of social-techno-political and Earth's climate system are irreducibly uncertain (Reilly, 2001; Smith and Stern, 2011). The EPS model, with a run time of less than 0.1 seconds on our hardware, is an intriguing candidate for a model combining comprehensiveness, extensive uncertainties and high performance.

Many other integrated models in the energy and climate domains take hours or days to run, limiting the ability of modellers to explore these systemically. With such a fast model, it is surprising that even EPS's technical documentation (see Section A.2) recommends only testing different parameters for at most 10 different policies simultaneously or otherwise just comparing policy packages. We believe that modellers should favour addressing uncertainty over complexity, especially given recent advances in computational power and the accessibility of low-cost cloud computing.

Model Diversity and Transparency

EPS is a model with integration errors, a focus on technology approaches to climate mitigation, and a very influential industrial carbon tax. Yet, all models contain their biases and sets of parametric and structural assumptions. (Thompson and Smith, 2019) iterate that models are not only chaotically sensitive to initial conditions, but also to structures. Jaxa-Rozen and Trutnevyte (2021), in a review of 1,550 scenarios, showed that solar photovoltaic technology forecasts are highly dependent on the type of organization, model, and policy assumptions. (Oreskes, Shrader-Frechette, and Belitz, 1994) also argue that it is impossible to ever validate large and complex models, like energy system ones. Therefore, we find it critically important for the energy modelling community in Canada and elsewhere to reasoning across a model ensemble (Bankes, 1993), a practice seen in other domains (e.g. (Taylor, Stouffer, and Meehl, 2012)). Furthermore, we also recognize the importance of open-source modelling, which is critical to scientific rigour through reproducibility and peer review (Nikolic et al., 2019). Models or ensembles that are more transparent are more credible for use in policy.

In scan of the Energy Modelling Institute's inventory of models that allow national energy-GHG policy analysis, we found five simulation models, of which only one is open-source (ours):

- gTech, calibrated to 2020 for most sectors and commonly used across Canada,
- CanESS, also an SD model, but that runs on a boutique proprietary software and is calibrated to 2013,
- E3MC, developed by Environment and Climate Change Canada and updated to 2020,
- Energy System Optimization Model, a model possibly used to support just one peer-reviewed article (Zhou et al., 2015), and
- EPS

We looked for the simulation tag specifically because it is needed to perform exploratory analysis, though optimization models can also be converted into simulation models (e.g. Lingeswaran (2019) adapted DICE (Nordhaus, 2014) for scenario discovery and other Deep Uncertainty approaches). We encourage future work to assess model ensembles.

Data and Model Limitations Since this study focused on model analysis methods, we only briefly review data limitations. The data itself does not jeopardize our approach, but could influence our conclusions. EPS has been in active development but only most recently updated in 2019. Its data are from 2016-2017 to allow Pan-Canadian Framework policies to compare against their absence. Neither its structures nor its data reflect recent developments in industry, policy, and science. As noted previously, all of its data is gathered from government sources and American data are used in lieu of unavailable Canadian data.

Similarly, we did not deeply investigate the model structure or verify or validate it beyond understanding the integration errors we found. One source of these errors was that the model defines a minimum contribution of natural gas peaker plants to the electricity grid, but our scenarios had widespread and large uptake in distributed solar photovoltaics that reduced grid demand below that peaker plant minimum. Experts could likely argue both for and against this type of scenario.

Because the oil sands limit control is not defined as a boolean in the Vensim model, our analysis could not consider this policy. Instead, it is defined as a policy implemented over time that overrides all industrial emissions output in the model to enforce the cap's effect. We would have needed to add a new variable, which would take time to verify and validate, and overwrite one of the input data files but with the oil sand limit removed. Moreover, this model does not allow one to change the emissions limit, but rather just whether it fits with the 100 Mt limit or not. A greater question from policymakers would be what the cap should be.

Policy Limitations The most conventionally obvious policy limitation in this version of the EPS model is that it may not include some policy structures that policies suggested beyond the 2016 Pan-Canadian Framework might entail. Though we argued earlier that uncertainty treatment is the most important limitation for policy usefulness, none of the policy combinations can lead to net-zero emissions by 2050 in this model. As Canada has now announced a net-zero target, it illuminates the limitations of this model to explore options to meet the current policy objectives and suggests it may need to be updated to be relevant.

It is also important to note that this model does not account for structural changes in energy markets, like electricity market reform or feed-in-tariffs explicitly, mechanisms like percent adoption of distributed solar photovoltaics can act as proxies, just as a flat economy-wide carbon price can approximate the impacts of policies like cap and trade systems, but further investigation of the model structural is required to verify this approach. Donges et al. (2018) and Otto et al. (2020) criticize integrated modelling for energy and climate policy to overly favouring technology, and instead challenge the field to consider how policy changes may have social effects (and vice versa), which could change model parameters and structures.

4.3. State of Work and Future Research

We have given some initial glimpses into how exploratory modelling can be applied to energy models in general, and the EPS in particular. A number of future research directions can be envisioned. Scenario discovery could be performed for alternative success conditions, such as combinations of environmental, fiscal and social targets. On the model side, EPS can be updated to version 3 (already available for the United States of America) to include more recent policy considerations and macroeconomic outputs, like GDP and jobs that are important to policy analysis. Also updating data parameters can offer outputs directly comparable to current policy discussions, which could improve the persuasiveness of outcomes; model complexity is relevant to decision-makers' intuitions and exploratory modelling asks for a broader paradigm shift in how models are used and communicated.

Most importantly, for these authors and the broader energy modelling community, Deep Uncertainty approaches can not only mitigate some of the most critical issues in the domain, but can also add value in other ways. Recently, Deep Uncertainty techniques that extend scenario discovery to finding robust policy *pathways* have been used to plan the future of Rotterdam's port collaboratively with stakeholders (Cuppen et al., 2020). This project also showcased how Deep Uncertainty approaches can be used to incorporate vastly different social, technical, and political perspectives in a participatory and constructive framework. A similar approach can be easily applied to complex Canadian challenges across the country. Lempert (2018) argue that Deep Uncertainty is critical for developing Long Term Strategies, an approach Canada has not taken to-date.

5. Conclusion

Using a simulation model of energy and climate, we show through exploratory modelling that a carbon tax on industry of at least $270 CAD/tCO2e is the most important policy lever for reducing GHG emissions 80% in Canada 2050 while costing nothing or only saving money across households, industry, and government. To minimize the cost of policy packages, electricity transmission capacity should be built – but not more than 115% what would have without intervention. Apart from innovation encouraged by the carbon tax, resources should be directed specifically to innovation in the building insulation to drive its cost down at least 19%. Around half of our results outperform the policy package that won the 2019 Pembina Institute Youth Policy Design Competition while using only three policies and accounting for uncertainties in all other parameters, showing that our approach can generate robust results with minimal analyst bias and save time and money spent on incrementally analyzing models and updating them frequently to match data changes. The value of systematic model exploration is further cemented by the fact that we discovered technical errors in the model during our research. This shows that exploratory modelling maximizes the return on investment in creating simulation models of complex societal problems by systematically exploring their parameters, structure and behavior. Future work for this model include updating it to more recent specifications and data, especially to analyze policies and targets announced after the initial Pan-Canadian Framework, and apply more advanced design algorithms to identify robust and adaptive decarbonization policy pathways. We also call for more model diversity and ensemble analysis within the energy modelling domain to further minimize modelling biases and provide better policy analysis.

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A. Appendix

A.1. Nomenclature

Acronym	Definition
GHG	Greenhouse gas
PRIM	Patient Rule-Induction Method
EPS	Energy Policy Simulator (Solutions)
EMA Workbench	Exploratory Modelling and Analysis Workbench
tCO2e	Tons of carbon dioxide-equivalent (GHG emisisons)
YPDC	Youth Policy Design Competition

A.2. Policy Levers and Ranges

We used 184 levers in the EPS model. The table below details all of these, separated by eight sectors: transportation; buildings; electricity; industry; agriculture, land use, and forestry; district heat, cross-sector, and research and development. Technical documentation on the EPS model, which explains these parameters and related assumptions, is hosted at https://us.energypolicy.solutions/docs/index.html.

Table 1: Model Parameters and Ranges

Parameter Name	Parameter Type	Minimum	Maximum
Transportation Sector Policies			
Percentage Reduction of Separately Regulated Pollutants[LDVs]	Real	0	1
Percentage Reduction of Separately Regulated Pollutants[HDVs]	Real	0	1
Percentage Reduction of Separately Regulated Pollutants[aircraft]	Real	0	1
Percentage Reduction of Separately Regulated Pollutants[rail]	Real	0	1
Percentage Reduction of Separately Regulated Pollutants[ships]	Real	0	1
Percentage Reduction of Separately Regulated Pollutants[motorbikes]	Real	0	1
Boolean EV Perks	Categorical	0	1
Additional Minimum Required EV Sales Percentage[passenger LDVs]	Real	0	1
Additional Minimum Required EV Sales Percentage[freight LDVs]	Real	0	1
Additional Minimum Required EV Sales Percentage[passenger HDVs]	Real	0	1
Additional Minimum Required EV Sales Percentage[freight HDVs]	Real	0	1
Additional Minimum Required EV Sales Percentage[passenger motorbikes]	Real	0	1
Additional EV Subsidy Percentage[passenger LDVs]	Real	0	1
Additional EV Subsidy Percentage[freight HDVs]	Real	0	1
LDVs Feebate Rate	Real	0	1
Percentage Additional Improvement of Fuel Economy Std[gasoline vehicle LDVs]	Real	0	1
Percentage Additional Improvement of Fuel Economy Std[diesel vehicle HDVs]	Real	0	1
Percentage Additional Improvement of Fuel Economy Std[nonroad vehicle aircraft]	Real	0	1
Percentage Additional Improvement of Fuel Economy Std[nonroad vehicle rail]	Real	0	1
Percentage Additional Improvement of Fuel Economy Std[nonroad vehicle ships]	Real	0	1
Percentage Additional Improvement of Fuel Economy Std[gasoline vehicle motorbikes]	Real	0	1
Additional LCFS Percentage	Real	0	1
Fraction of TDM Package Implemented[passenger]	Real	0	1
Fraction of TDM Package Implemented[freight]	Real	0	1
Buildings Sector Policies			
Percent New Nonelec Component Sales Shifted to Elec[urban residential]	Real	0	1
Percent New Nonelec Component Sales Shifted to Elec[rural residential]	Real	0	1
Percent New Nonelec Component Sales Shifted to Elec[commercial]	Real	0	1

Table 1 continued from previous page

Parameter Name	Parameter Type	Minimum	Maximum
Reduction in E Use Allowed by Component Eff Std[heating urban residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[cooling and ventilation urban residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[envelope urban residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[lighting urban residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[appliances urban residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[other component urban residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[heating rural residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[cooling and ventilation rural residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[envelope rural residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[lighting rural residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[appliances rural residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[other component rural residential]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[heating commercial]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[cooling and ventilation commercial]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[envelope commercial]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[lighting commercial]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[appliances commercial]	Real	0	1
Reduction in E Use Allowed by Component Eff Std[other component commercial]	Real	0	1
Boolean Improved Contractor Edu and Training	Categorical	0	1
Min Fraction of Total Elec Demand to be Met by Distributed Solar PV	Real	0	1
Perc Subsidy for Distributed Solar PV Capacity	Real	0	1
Boolean Improved Device Labeling	Categorical	0	1
Fraction of Commercial Components Replaced Annually due to Retrofitting Policy[heating]	Real	0	1
Fraction of Commercial Components Replaced Annually due to Retrofitting Policy[cooling and ventilation]	Real	0	1
Fraction of Commercial Components Replaced Annually due to Retrofitting Policy[envelope]	Real	0	0.1
Fraction of Commercial Components Replaced Annually due to Retrofitting Policy[lighting]	Real	0	0.1
Fraction of Commercial Components Replaced Annually due to Retrofitting Policy[appliances]	Real	0	0.1
Fraction of Commercial Components Replaced Annually due to Retrofitting Policy[other component]	Real	0	0.1
Boolean Rebate Program for Efficient Components[heating]	Categorical	0	1
Boolean Rebate Program for Efficient Components[cooling and ventilation]	Categorical	0	1

Table 1 continued from previous page

Parameter Name	Parameter Type	Minimum	Maximum
Boolean Rebate Program for Efficient Components[appliances]	Categorical	0	1
Electricity Sector Policies			
Boolean Ban New Power Plants[hard coal es]	Categorical	0	1
Boolean Ban New Power Plants[natural gas nonpeaker es]	Categorical	0	1
Boolean Ban New Power Plants[hydro es]	Categorical	0	1
Percent Change in Electricity Exports	Real	-0.5	1
Percent Change in Electricity Imports	Real	-0.5	1
Fraction of Additional Demand Response Potential Achieved	Real	0	1
Annual Additional Capacity Retired due to Early Retirement Policy[hard coal es]	Real	0	10000
Annual Additional Capacity Retired due to Early Retirement Policy[nuclear es]	Real	0	10000
Additional Battery Storage Annual Growth Percentage	Real	0	1
Percentage Increase in Transmission Capacity vs BAU	Real	0	2
Boolean Use Non BAU Mandated Capacity Construction Schedule	Categorical	0	1
Nuclear Capacity Lifetime Extension	Real	0	30
Percentage Reduction in Plant Downtime[natural gas nonpeaker es preexisting retiring]	Real	0	1
Percentage Reduction in Plant Downtime[onshore wind es newly built]	Real	0	1
Percentage Reduction in Plant Downtime[solar PV es newly built]	Real	0	1
Percentage Reduction in Plant Downtime[offshore wind es newly built]	Real	0	1
Percent Reduction in Soft Costs of Capacity Construction[onshore wind es]	Real	0	1
Percent Reduction in Soft Costs of Capacity Construction[solar PV es]	Real	0	1
Percent Reduction in Soft Costs of Capacity Construction[offshore wind es]	Real	0	1
Percentage TnD Losses Avoided	Real	0	1
Additional Renewable Portfolio Std Percentage	Real	0	1
Subsidy for Elec Production by Fuel[nuclear es]	Real	0	100
Subsidy for Elec Production by Fuel[onshore wind es]	Real	0	100
Subsidy for Elec Production by Fuel[solar PV es]	Real	0	100
Subsidy for Elec Production by Fuel[solar thermal es]	Real	0	100
Subsidy for Elec Production by Fuel[biomass es]	Real	0	100
Subsidy for Elec Production by Fuel[offshore wind es]	Real	0	100

Table 1 continued from previous page

Parameter Name	**Parameter Type**	**Minimum**	**Maximum**
Subsidy for Elec Production by fuel[geothermal es]	Real	0	100
Industry Sector Policies			
Fraction of Cement Clinker Substitution Made	Real	0	1
Fraction of Potential Cogeneration and Waste Heat Recovery Adopted	Real	0	1
Fraction of Energy Savings from Early Facility Retirement Achieved	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[cement and other carbonates]	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[natural gas and petroleum systems]	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[iron and steel]	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[chemicals]	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[mining]	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[waste management]	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[agriculture]	Real	0	1
Percentage Improvement in Eqpt Efficiency Standards above BAU[other industries]	Real	0	1
Fraction of Hard Coal Use Converted to Other Fuels	Real	0	1
Fraction of Natural Gas Use Converted to Other Fuels	Real	0	1
Fraction of Methane Capture Opportunities Achieved	Real	0	1
Fraction of Methane Destruction Opportunities Achieved	Real	0	1
Fraction of F Gases Avoided	Real	0	1
Fraction of Addressable Process Emissions Avoided via Worker Training	Real	0	1
Agriculture Land Use and Forestry Policies			
Fraction of Afforestation and Reforestation Achieved	Real	0	1
Fraction of Avoided Deforestation Achieved	Real	0	1
Fraction of Forest Set Asides Achieved	Real	0	1
Fraction of Abatement from Cropland Management Achieved	Real	0	1
Fraction of Improved Forest Management Achieved	Real	0	1
Fraction of Abatement from Livestock Measures Achieved	Real	0	1
District Heat Sector Policies			

Table 1 continued from previous page

Parameter Name	Parameter Type	Minimum	Maximum
Fraction of Non CHP Heat Production Converted to CHP	Real	0	1
Cross-Sector Policies			
Fraction of Potential Additional CCS Achieved	Real	0	1
Carbon Tax[transportation sector]	Real	0	800
Carbon Tax[electricity sector]	Real	0	800
Carbon Tax[residential buildings sector]	Real	0	800
Carbon Tax[commercial buildings sector]	Real	0	800
Carbon Tax[industry sector]	Real	0	800
Percent Reduction in BAU Subsidies[hard coal]	Real	0	1
Percent Reduction in BAU Subsidies[natural gas]	Real	0	1
Percent Reduction in BAU Subsidies[petroleum gasoline]	Real	0	1
Percent Reduction in BAU Subsidies[petroleum diesel]	Real	0	1
Percent Reduction in BAU Subsidies[jet fuel]	Real	0	1
Additional Fuel Tax Rate by Fuel[electricity]	Real	0	1
Additional Fuel Tax Rate by Fuel[hard coal]	Real	0	1
Additional Fuel Tax Rate by Fuel[natural gas]	Real	0	1
Additional Fuel Tax Rate by Fuel[petroleum gasoline]	Real	0	1
Additional Fuel Tax Rate by Fuel[petroleum diesel]	Real	0	1
Research & Development Levers			
RnD Building Capital Cost Perc Reduction[heating]	Real	0	1
RnD Building Capital Cost Perc Reduction[cooling and ventilation]	Real	0	1
RnD Building Capital Cost Perc Reduction[envelope]	Real	0	1
RnD Building Capital Cost Perc Reduction[lighting]	Real	0	1
RnD Building Capital Cost Perc Reduction[appliances]	Real	0	1
RnD Building Capital Cost Perc Reduction[other component]	Real	0	1
RnD CCS Capital Cost Perc Reduction	Real	0	1
RnD Electricity Capital Cost Perc Reduction[hard coal es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[natural gas nonpeaker es]	Real	0	1

Table 1 continued from previous page

Parameter Name	Parameter Type	Minimum	Maximum
RnD Electricity Capital Cost Perc Reduction[nuclear es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[hydro es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[onshore wind es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[solar PV es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[solar thermal es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[biomass es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[natural gas peaker es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[lignite es]	Real	0	1
RnD Electricity Capital Cost Perc Reduction[offshore wind es]	Real	0	1
RnD Industry Capital Cost Perc Reduction[cement and other carbonates]	Real	0	1
RnD Industry Capital Cost Perc Reduction[natural gas and petroleum systems]	Real	0	1
RnD Industry Capital Cost Perc Reduction[iron and steel]	Real	0	1
RnD Industry Capital Cost Perc Reduction[chemicals]	Real	0	1
RnD Industry Capital Cost Perc Reduction[mining]	Real	0	1
RnD Industry Capital Cost Perc Reduction[waste management]	Real	0	1
RnD Industry Capital Cost Perc Reduction[agriculture]	Real	0	1
RnD Industry Capital Cost Perc Reduction[other industries]	Real	0	1
RnD Transportation Capital Cost Perc Reduction[battery electric vehicle]	Real	0	1
RnD Transportation Capital Cost Perc Reduction[natural gas vehicle]	Real	0	1
RnD Transportation Capital Cost Perc Reduction[gasoline vehicle]	Real	0	1
RnD Transportation Capital Cost Perc Reduction[diesel vehicle]	Real	0	1
RnD Transportation Capital Cost Perc Reduction[plugin hybrid vehicle]	Real	0	1
RnD Transportation Capital Cost Perc Reduction[nonroad vehicle]	Real	0	1
RnD Building Fuel Use Perc Reduction[heating]	Real	0	1
RnD Building Fuel Use Perc Reduction[cooling and ventilation]	Real	0	1
RnD Building Fuel Use Perc Reduction[lighting]	Real	0	1
RnD Building Fuel Use Perc Reduction[appliances]	Real	0	1
RnD Building Fuel Use Perc Reduction[other component]	Real	0	1
RnD CCS Fuel Use Perc Reduction	Real	0	1
RnD Electricity Fuel Use Perc Reduction[hard coal es]	Real	0	1

Table 1 continued from previous page

Parameter Name	Parameter Type	Minimum	Maximum
RnD Electricity Fuel Use Perc Reduction[natural gas nonpeaker es]	Real	0	1
RnD Electricity Fuel Use Perc Reduction[nuclear es]	Real	0	1
RnD Electricity Fuel Use Perc Reduction[biomass es]	Real	0	1
RnD Electricity Fuel Use Perc Reduction[natural gas peaker es]	Real	0	1
RnD Electricity Fuel Use Perc Reduction[lignite es]	Real	0	1
RnD Industry Fuel Use Perc Reduction[cement and other carbonates]	Real	0	1
RnD Industry Fuel Use Perc Reduction[natural gas and petroleum systems]	Real	0	1
RnD Industry Fuel Use Perc Reduction[iron and steel]	Real	0	1
RnD Industry Fuel Use Perc Reduction[chemicals]	Real	0	1
RnD Industry Fuel Use Perc Reduction[mining]	Real	0	1
RnD Industry Fuel Use Perc Reduction[waste management]	Real	0	1
RnD Industry Fuel Use Perc Reduction[agriculture]	Real	0	1
RnD Industry Fuel Use Perc Reduction[other industries]	Real	0	1
RnD Transportation Fuel Use Perc Reduction[battery electric vehicle]	Real	0	1
RnD Transportation Fuel Use Perc Reduction[natural gas vehicle]	Real	0	1
RnD Transportation Fuel Use Perc Reduction[gasoline vehicle]	Real	0	1
RnD Transportation Fuel Use Perc Reduction[diesel vehicle]	Real	0	1
RnD Transportation Fuel Use Perc Reduction[plugin hybrid vehicle]	Real	0	1
RnD Transportation Fuel Use Perc Reduction[nonroad vehicle]	Real	0	1

A.3. Global sensitivity analysis results

Table 2: Sensitivities for *Output Cumulative Total CO2e Emissions*

	ST	ST_conf	S1	S1_conf
Carbon Tax[industry sector]	0.934978	0.063026	0.936931	0.071889

Table 3: Sensitivities for *Output Total CO2e Emissions*

	ST	ST_conf	S1	S1_conf
Carbon Tax[industry sector]	0.898166	0.069218	0.901834	0.070047

Table 4: Sensitivities for *Output Change in Government Cash Flow*

	ST	ST_conf	S1	S1_conf
Additional EV Subsidy Percentage[passenger,LDVs]	0.141389	0.014700	0.116542	0.030473
Additional Fuel Tax Rate by Fuel[electricity]	0.081676	0.007543	0.070674	0.024962
Carbon Tax[industry sector]	0.449829	0.042525	0.435744	0.058893
Carbon Tax[transportation sector]	0.154214	0.013746	0.157570	0.033529

Table 5: Sensitivities for *Output Change in Industry Cash Flow*

	ST	ST_conf	S1	S1_conf
Carbon Tax[industry sector]	0.279880	0.028881	0.214095	0.053106
Percentage Improvement in Eqpt Efficiency Stand...	0.057861	0.006800	0.069925	0.020066
Percentage Increase in Transmission Capacity vs...	0.218258	0.022310	0.197090	0.044996
RnD Building Capital Cost Perc Reduction[envelope]	0.062850	0.006362	0.068474	0.022607
RnD Industry Fuel Use Perc Reduction[other indu...	0.096949	0.009030	0.090771	0.028404

Table 6: Sensitivities for *Output Change in Consumer Cash Flow*

	ST	ST_conf	S1	S1_conf
Additional EV Subsidy Percentage[passenger,LDVs]	0.084268	0.008790	0.069945	0.023158
Carbon Tax[industry sector]	0.161916	0.016048	0.165134	0.032964
Percentage Increase in Transmission Capacity vs...	0.051498	0.004312	0.049574	0.020988
RnD Building Capital Cost Perc Reduction[envelope]	0.374742	0.033647	0.369200	0.047268
RnD Transportation Capital Cost Perc Reduction[...	0.110573	0.011305	0.100347	0.026518
RnD Transportation Capital Cost Perc Reduction[...	0.085891	0.008685	0.078691	0.027014

Table 7: Sensitivities for *Output Total Change in Outlays with Revenue Neutral Carbon Tax*

	ST	ST_conf	S1	S1_conf
Percentage Increase in Transmission Capacity vs...	0.464429	0.039408	0.453963	0.053832
RnD Building Capital Cost Perc Reduction[envelope]	0.217331	0.020881	0.218640	0.037939
RnD Transportation Capital Cost Perc Reduction[...	0.085596	0.008889	0.081395	0.025458
RnD Transportation Capital Cost Perc Reduction[...	0.051707	0.006492	0.044520	0.018857

Table 8: Sensitivities for *Output Total Change in Outlays*

	ST	ST_conf	S1	S1_conf
Carbon Tax[industry sector]	0.134882	0.015800	0.124347	0.033574
Percentage Increase in Transmission Capacity vs...	0.386946	0.032629	0.379610	0.052061
RnD Building Capital Cost Perc Reduction[envelope]	0.184111	0.015003	0.185384	0.035961
RnD Transportation Capital Cost Perc Reduction[...	0.074677	0.007174	0.068285	0.025527

Table 9: Sensitivities for *Output Human Lives Saved from Reduced Particulate Pollution*

	ST	ST_conf	S1	S1_conf
Annual Additional Capacity Retired due to Early...	0.065847	0.010086	0.041678	0.022001
Carbon Tax[industry sector]	0.201997	0.021969	0.196913	0.036587
RnD Electricity Fuel Use Perc Reduction[biomass...	0.108212	0.013140	0.008696	0.027412
Subsidy for Elec Production by Fuel[biomass es]	0.511329	0.057114	0.396891	0.047434

Table 10: Sensitivities for *Output Social Benefits from Emissions Reduction*

	ST	ST_conf	S1	S1_conf
Carbon Tax[industry sector]	0.668757	0.048975	0.67325	0.069129
Subsidy for Elec Production by Fuel[biomass es]	0.154741	0.016519	0.11550	0.030749