Exploring the near-optimal solution space of an energy system optimization model

to evaluate similarly costly but techno-economically diverse decarbonization pathways

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Abstract

Energy system optimization models typically return one optimal solution per set of input parameters. However, given the nature of their mathematical formulation, there exist many near-optimal solutions. These near-optimal solutions – similar in cost but diverse in technology portfolios – can give stakeholders involved with the energy system planning process a more diverse set of decarbonization pathways to evaluate. In fact, sub-optimal solutions may ultimately be preferred by decision makers for a number of features that are not easily translated into model inputs, such as issues relating to social acceptance and equity. This project introduces the modelling to generate alternatives methodology to systematically explore the near-optimal solution space of an energy system optimization model of Western Canada. The modelling project leverages existing open-source software and serves as an illustrative guide on how the modelling to generate alternatives methodology can be used to make the energy system planning process more robust.

Résumé

Les modèles d'optimisation du système énergétique renvoient généralement une solution optimale par ensemble de paramètres d'entrée. Cependant, étant donné la nature de leur formulation mathématique, il existe de nombreuses solutions quasi optimales. Ces solutions quasi optimales - similaires en termes de coût mais diversifiées dans les portefeuilles technologiques - peuvent donner aux parties prenantes impliquées dans le processus de planification du système énergétique un ensemble plus diversifié de voies de décarbonation à évaluer. En fait, les solutions sous-optimales peuvent finalement être préférées par les décideurs pour un certain nombre de caractéristiques qui ne sont pas facilement traduites en entrées de modèle, telles que les questions liées à l'acceptation sociale et à l'équité. Ce projet introduit la modélisation pour générer une méthodologie alternative pour explorer systématiquement l'espace de solution quasi optimal d'un modèle d'optimisation du système énergétique de l'Ouest canadien. Le projet de modélisation tire parti des logiciels open source existants et sert de guide illustratif sur la façon dont la modélisation pour générer des méthodes alternatives peut être utilisée pour rendre le processus de planification du système énergétique plus robuste.

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1 Introduction

Climate change mitigation efforts consistent with reaching the targets established under the Paris Agreement will require complete overhauls of energy systems around the world. This will include an enormous build-out of new technologies as well as the accelerated retirement and decommissioning of existing polluting technologies. It's likely that considerable pressure will be placed on the electricity sector in particular as the electrification of end-use technologies continues apace.

Electricity generation and transmission infrastructure are capital intensive and long-lived assets. The investment decisions faced today by officials must be made in the face of deep uncertainty about the future of technology costs, technological breakthroughs, demand patterns, geopolitical realities and other macro-economic considerations. A critical challenge is therefore to develop robust tools and frameworks for dealing with planning in uncertain environments.

Energy system models are a central decision support tool used in such planning contexts. Energy system planning models are formulated as constrained convex optimization problems[1] that seek the set of investment, retirement and operational decisions that minimize the total discounted system costs or maximize surplus. These models typically have a regional to continental scope and look several decades into the future. Energy system modellers have throughout the years developed methods to systematically quantify, understand, and process the uncertainty involved with the planning problem and the models themselves.

Model uncertainties can be separated into parametric and structural uncertainties [1, 2]. Parametric uncertainty relates to the modeller's inability to know future prices, discount rates, and other energy system model input parameters. Most popular methods for dealing with uncertainty in energy system models – such as scenario analysis, sensitivity analysis, and stochastic optimization – deal directly with parametric uncertainty. Structural uncertainty, on the other hand, refers to the manifestations of the mathematical abstractions encoded in the computational model. Modelling to generate alternatives

[1] typically linear or mixed integer linear programs.

(MGA) has been suggested [3, 4] as a means to deal with structural uncertainty by systematically exploring the near-optimal solution space and selecting from it alternative solutions that are distinct from the optimal solution in metrics defined by the modeller. The intent of MGA is then not to provide a singular answer, but to provide a set of alternative solutions that exhibit the degree of flexibility in the model solution and can be further analysed. This deliberately counteracts energy system modelling artefacts such as solutions sitting on a knife-edge and penny-switching.

Using the MGA methodology in the energy systems application dates back to 2011 [5]. The method has since become increasingly popular in the modelling community, e.g. [6, 7, 8]. Two recent publications are particularly relevant as they evince the insights MGA can lend to the energy system modelling practice and, specifically, to this project. Lombardi et al. [9] use MGA in a power system planning model of Italy to study issues related to the spatial distribution of generation and transmission projects. The authors explore the near-optimal solution space by searching for solutions that are maximally distinct in their spatial configurations (e.g. concentration of wind turbines or capacities of transmission corridors). Presenting the results in such a regionalized manner is constructive for the decision making process as the relevant legislative power in Italy belongs to the regional governments – much like the Canadian case.

Neumann and Brown [10] use MGA in a European-wide power system planning model to look at how the capacities of each technology can deviate if the total system costs are allowed to marginally increase. The authors systematically explored 384 near-optimal solutions and uncover general trends and insights such as the complementarity or substitutability of certain technology pairs.

To the best of our knowledge, there has been no such application of MGA or other methods to deal with structural uncertainty of energy system optimization models in the Canadian context[2].

This project outlines the MGA methodology before applying it to explore near-optimal solutions to an energy system model of Western Canada. The objective is to exhibit the

[2]This is distinct from parametric uncertainty, for which there are a number of great studies.

ways in which MGA can compliment and add to existing energy system modelling efforts in Canada by providing decision makers with a portfolio of energy system transitions that are distinct in meaningful and easily digestible ways, and communicate the levels of uncertainties involved with long term energy system planning.

2 The model

2.1 Modelling to generate alternatives

Most energy system optimizations models – be they capacity expansion models, production cost models, or any other family of models – are at their core convex optimization problems. The models minimize some objective function subject to a set of constraints, where both the objective functions and constraints are convex, e.g. linear. A convex optimization problem written in standard form is shown in Equation (1).

$$\begin{aligned} \underset{\vec{x}}{\text{minimize}} \quad & f(\vec{x}) \\ \text{subject to} \quad & g_i(\vec{x}) \leq 0 \\ & h_i(\vec{x}) = 0 \end{aligned} \tag{1}$$

In the case of the energy system planning, or 'capacity expansion' problem, the objective function is to minimize the annual system costs, comprised of annualised capital costs and fixed and variable operating costs. The *decision variables* – or, the variables that are to be optimized by the model – are encoded into the vector $\vec{x}$. Decision variables for capacity expansion problems encompass investment, retirement and operating decisions of the technologies. Other details important to capacity expansion models, such as costs, lifetimes, and efficiencies, are encoded as *parameters* and are not central to this discussion.

What's important is that given a set of input parameters, optimization solvers are designed to find the unique optimal solution to the problem. In the capacity expansion context, this means that each model scenario (encoded as a set of input parameters and constraints) results in the single, least-cost portfolio of investment and operational deci-

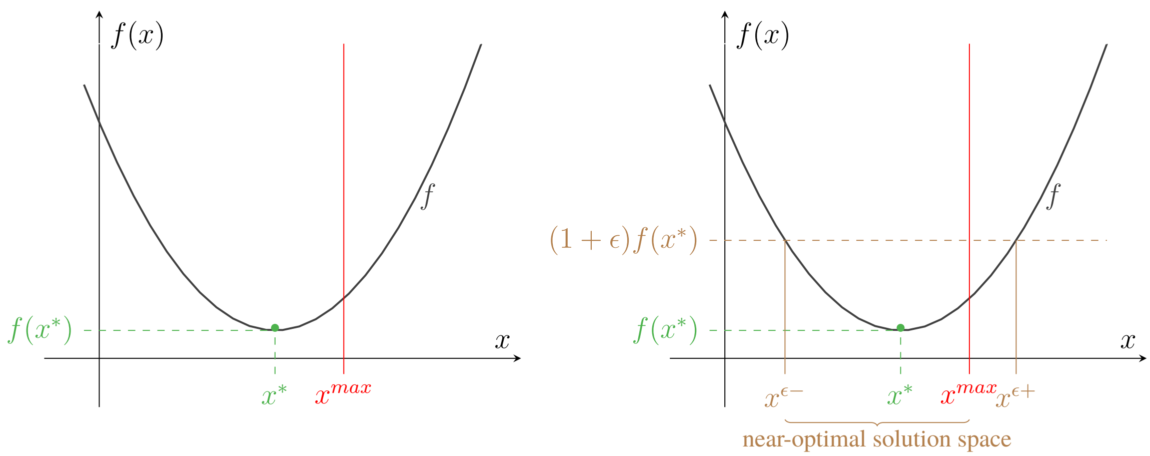


Figure 1: Schematic of the MGA methodology.

sions (optimal solution). By their very definition, however, convex optimization problems are guaranteed to have innumerable sub-optimal solutions that are arbitrarily close to the optimal solution. Near-optimal solutions may be of interest to modellers for a variety of reasons, not least because they provide alternative pathways at a small increase in cost.

MGA is a systematic methodology to explore the near-optimal solution space of the optimization problem. To better illustrate the MGA methodology, the following one dimensional (i.e. $\vec{x} = x$) example is considered.

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & f(x) \\ \text{subject to} \quad & x - x^{max} \leq 0 \end{aligned} \tag{2}$$

That is, the problem seeks to minimize some function $f(x)$ for all values of x less than or equal to some parameter x^{max}. This is illustrated in Figure 1 (left).

TEST The MGA methodology can be thought of as a three step process that begins by solving the optimization problem in (2) to find the optimal solution, x^*. The second step is to define the near-optimal solution space. This is done by using the solution x^* as an anchor point. Given a slack parameter ϵ – think of it as the length of the rope attached to the anchor – the following constraint defines the near-optimal solution space.

$$f(x) \leq (1+\epsilon)f(x^*) \tag{3}$$

That is, the original solution space is further constrained to the set of values of x that result in at most an ϵ percent increase to the original objective function. This is illustrated in Figure 1 (right), where $x^{\epsilon-}$ and $x^{\epsilon+}$ are the newly introduced constraints that result from Equation (3).

With the objective function of the original optimization problem (2) now encoded as a constraint to an updated optimization problem, the final step in the MGA methodology is to determine how to parse through the near-optimal solution space for near-optimal solutions. This strategy is determined by the modeller and is encoded as the objective function, $m(x)$, to the updated optimization problem in (4).

$$\begin{aligned} \underset{x}{\text{minimize}} \quad & m(x) \\ \text{subject to} \quad & x - x^{max} \leq 0 \\ & f(x) - (1+\epsilon)f(x^*) \leq 0 \end{aligned} \tag{4}$$

To continue the illustrated example, consider the following two choices for the new objective function: $m(x) = x$ and $m(x) = -x$. That is, the updated problem seeks to maximize x ($m(x) = x$) or minimize x ($m(x) = -x$) so long that x is in the near-optimal solution space. The respective solutions to the updated problems are then $x^{\epsilon-}$ and x^{max}, as illustrated in the figure. Although the outlined 1-dimensional example is great for illustrative purposes, practical use cases, such as energy system optimization models, contain millions of decision variables. There exist, then, many options for the choice of $m(x)$. Several methods exist to explore this space for interesting alternative solutions.

The 'hop-skip-jump' MGA methodology first introduced in 1982 by Brill et al. [11] for use in land-use planning problems prescribes an iterative approach to defining $m(x)$. The objective is to find a solution whose decision variables assume maximally different values than those of x^*. That is, $m(x)$ is encoded into the updated optimization problem (4) such that its solution is the point in the near-optimal space that is as different as possible to the original solution. Hop-skip-jump MGA has been used by DeCarolis et al. [12] on a capacity expansion model to examine maximally distinct transition pathways.

This project, in line with the methodology introduced by Neumann and Brown [10], instead defines the search directions by pre-defined groups of variables. In the capacity expansion context, this means searching the near-optimal solution space for solutions that minimize or maximize the total investment in or electricity generation from clearly defined groups of technologies, e.g. solar. Section 2.4 discuses in detail the way in which MGA is applied to the capacity expansion model outlined below.

2.2 The energy system optimization model

A capacity expansion model is developed to explore pathways of the electricity sectors of Alberta and British Columbia for the years 2020-2050. The model is coupled to the transportation sector in British Columbia by considering the electrification of the province's entire road fleet by 2050.

The model of the British Columbia electricity and transportation sectors is adapted from a previous study from the Institute for Integrated Energy Systems at the University of Victoria [13]. Similarly, the model of the Alberta electricity sector is adapted from [14]. The original models were developed in the OSeMOSYS energy system modelling framework [15] and have for this project been updated, coupled and transcribed into the Temoa energy system modelling framework [16]. Temoa is preferred to OSeMOSYS for this use case because it has a dedicated module for MGA.

A schematic of the energy system representation used in the model is given in Figure 2. The model is driven by exogenously defined demands for two types of energy services: electricity demand and transportation demand. These demands are met using technologies defined by their efficiencies; capital costs; fixed and variable operating; resource consumption rate (e.g. for coal plants) or availability (e.g. for wind turbines); lifetime; and associated operating or planning constraints. Resources are assigned a cost, energy density, and emissions intensity. The electricity demand is met by a collection of electricity generators whereas the transportation demand, expressed in millions of kilometres travelled, is met by a fleet of vehicles. The electricity and transportation sectors are coupled by battery electric vehicles, and the two provinces' electricity systems are connected by a 1 GW transmission line subject to possible expansion.

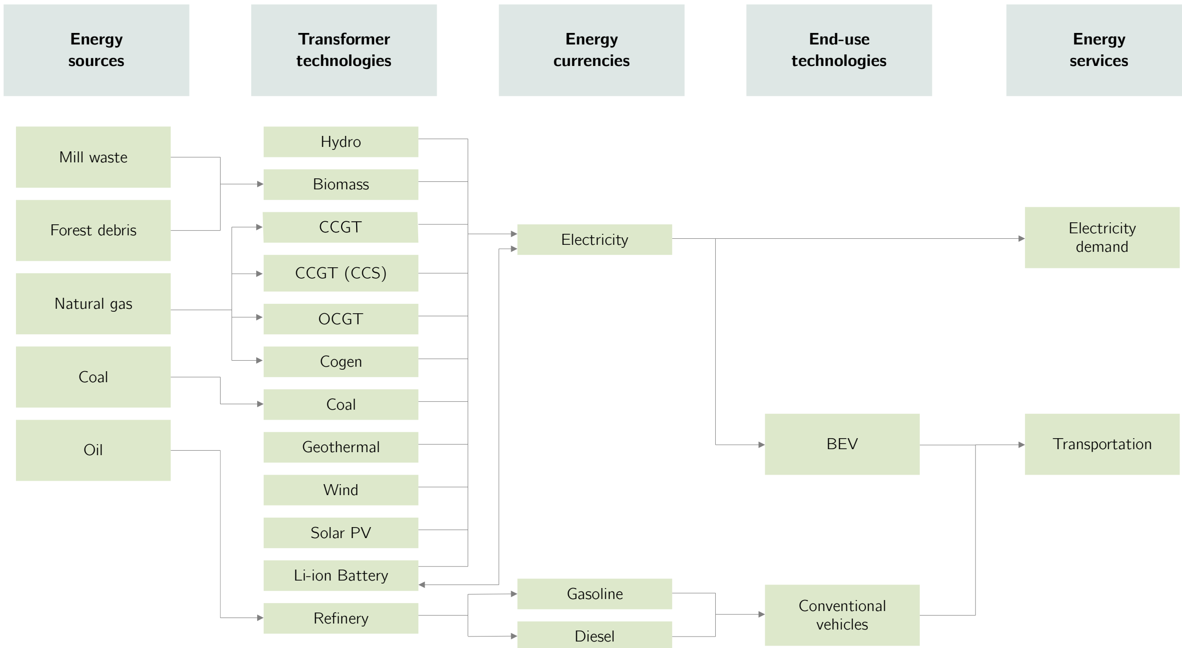


Figure 2: Schematic of the coupled Alberta and British Columbia system.

Under this framework, the model optimizes the planning and operational or dispatch decisions such that demand is met in every time step at a least cost, while bound to satisfy a set of constraints.

2.2.1 Technology options

Alberta Thermal generators in Alberta include coal, natural gas and biomass. Natural gas plants consist of cogeneration (cogen), combined cycle gas turbines (CCGT), open cycle gas turbine (OCGT) and combined cycle gas turbines with carbon capture and storage (CCGT-CCS) with 90% capture efficiency. Thermal generators consume fuels with exogenously defined costs for the model period. In addition to thermal generators, the following generation and storage technologies are defined: single-axis tracking solar photovoltaic; wind turbines; small hydro; and two- and four-hour battery energy storage.

In addition to serving electricity demand, generators must also meet a 15% reserve margin constraint consistent with the 2017 AESO Longterm Outlook. Thermal and hydro generators are assumed to provide 100% of their nameplate capacity to the reserve margin while wind power contributes 15% of its nameplate capacity and solar PV and batteries contribute 0%.

British Columbia Thermal generators in British Columbia include NGCC, NGCC-CCS, OCGT, biomass and geothermal. The hydroelectric system in the province is divided into two classes of generators: run-of-river (ROR) hydro and storage hydro (hydro). ROR hydro is modelled similar to variable renewable resources in that it is must-take and assigned a capacity factor reflecting historical output levels. Similar to the ROR technology, a portion of the storage hydro is considered 'must run' to reflect seasonal constraints on the hydroelectric system. The remaining portion of storage hydro is flexible and can be optimally dispatched so long as a prescribed annual energy budget is realized. Wind, one-axis tracking solar PV and two- and four-hour battery energy storage technologies are also included in the British Columbia model.

The reserve margin for British Columbia is 14%, reflecting BC Hydro's most recent integrated resource plan. Storage hydro and thermal generators provide 100% of their nameplate capacity to the reserve margin, whereas, in accordance with BC Hydro estimates, wind contributes 26% and ROR hydro contributes 10%. Selected generator characteristics are provided in Table 1.

The transportation sector is sub-divded into five classes: heavy-freight, medium-freight, light-freight, passenger vehicles and transit. Each class contains several vehicle types which are each prescribed a demand, fuel consumption rate and lifetime. Fuel switching from internal combustion engine vehicles to battery electric counterparts is exogenously defined for this model which contributes to overall demand for electricity. Technical characteristics and assumptions from the transportation sector are not included in this report in the interest of brevity. Interested readers should consult [13] for detailed information.

Technology	Capital cost 2020 [$/kW]	Capital cost 2050 [$/kW]	FOM [$/kW-yr]	VOM [$/MWh]	Efficiency [%]	Lifetime [yr]
Biomass	3485	3790	112.2	5.58	25.3	20
Coal	–	–	39.5	4.67	37	40
Cogen	–	–	9.9	1.99	70	40
Geothermal	–	6035	119.9	–	–	40
CCGT	1237	1060	17.67	3.54	53	30
CCGT (CCS)	3131	2297	33.75	7.08	45	30
OCGT	1130	969	6.87	10.81	35	30
Hydro (AB)	2442	2442	14.93	2.66	–	80
Hydro (BC)	2898	2898	13.42	5.95	–	80
Wind	2031	1242	46.71	–	–	25
Solar PV	1637	832	19.2	–	–	25
Battery (2h)	1037	437	44	–	85	15
Battery (4h)	1760	742	44	–	85	15
Transmission	820	820	0	–	95	80

Table 1: Selected technology parameters.

2.2.2 Spatial structure

Alberta is modelled as a single node with the exception of wind and solar PV resource sites. Seven resource zones are modelled for wind generation and four resource zones for solar PV generation. The Alberta electricity system is connected to the British Columbia electricity system via a transmission line with an effective capacity of 1 GW. The model allows for transmission system expansion. Similar to Alberta, British Columbia is modelled as a single zone with four wind resource sites and one solar PV resource site. Existing wind and solar resources sites for each province are also included. The model does not consider interconnections to other electricity markets.

2.2.3 Temporal structure

The model period extends from 2020-2050, with every fifth year explicitly included in the model. Each model year (2020, 2025, 2030, . . . , 2050) consists of ten representative days. The days are selected and scaled by weighting factors in order to preserve statistical characteristics important to electricity systems, e.g. peak net-load and the profiles of load, solar production, and wind production duration curves. The representative days and corresponding weights are selected via the optimization approach outlined in [17]. Each representative day consists of 24 periods, resulting in 240 time steps per model year.

To capture the seasonal attributes of hydroelectricity, representative days are assigned to each of one of three hydro seasons: peak-freshet (June), shoulder-freshet (May and July) and off-freshet (remaining months). Each season establishes minimum generation requirements for the hydro generators.

2.3 Data sources and availability

The MGA methodology requires no data itself. This section therefore outlines the data sources and availability of the energy system model.

Hourly electricity demand for 2019 is available for both the British Columbia and Alberta internal load. This is used to structure the hourly electricity demand profiles and inform the representative day selection algorithm. Determining the electricity load growth for British Columbia is done using the same method in [13], where the authors make use of data in the 2012 BC Hydro *Electric Load Forecast* and make adjustments to reflect double counting of projected electric vehicle load. Electricity load growth data for Alberta is based off the AESO 2017 Long Term Outlook.

Annual electric load growth attributed to electrifying British Columbia's road transportation fleet by 2050 is outlined in [13] and is based on an exponential regression method applied to the past 20 years of demand data for each class of vehicles [18]. Heavy-duty freight and transit are assumed to have constant charging profiles, whereas the EV charging profiles for passenger vehicles and medium- and light-freight vary throughout the day. The time varying profiles – which are distinct for weekends and weekdays – are taken from [19].

All data for the electricity sector is taken from [14] and [13] and updated with values from the National Renewable Energy Laboratory 2020 Annual Technology Baseline [20] with a 1.21 exchange rate for included technologies.

Wind and solar generation profiles are derived using the MERRA-2 global weather database with technology power curves applied [21]. Fuel costs for both the transportation and electricity sectors are based on the Energy Information Agency 2017 Annual Energy Outlook.

The model includes existing electricity generating and inter-provincial transmission capacity and accounts for planned retirement dates. The total capacity of storage hydro in British Columbia is capped after the assumed addition of Site-C. ROR hydro in British Columbia is capped at a total of 6 GW. Similarly, geothermal and biomass capacities are capped at a maximum of 1 GW and 1.2 GW, respectively, to reflect resource constraints. In Alberta, no new capacity of cogen or coal is allowed and the hydro resource is capped at 0.89 GW.

2.4 Scenario development and MGA application

This project looks at decarbonization pathways that lead to a fully electrified road transportation fleet in British Columbia by 2050. The electricity demand from electric vehicles is prescribed exogenously as in [13]. Aside from the EV mandate, the federal carbon tax (as of March 2021) and a coal phase out by 2030 in Alberta are included. No other policy constraints are considered.

Traditionally, scenario analyses are used to evaluate the parametric uncertainty in the model and to draw out insights on how sensitive the model outputs are to the input data. This project, on the other hand, uses the MGA methodology to uncover and evaluate the model's structural uncertainty. Once the main scenario is run, the MGA methodology is used to explore the near-optimal solution space to find solutions that maximize and minimize total activity of technology groups.

Specifically, the MGA application allows the following question to be answered: relative to the base model, how much more or less electricity can be be generated from a certain technology group over the model period at a prescribed cost premium? This question is answered for the following groups of technologies:

1. Wind

2. Solar

3. Batteries (both 2h and 4h)

4. Transmission (i.e. the total amount of electricity traded between Alberta and British Columbia)

5. CCGT (both with and without CCS)

and for the following slack values $\epsilon \in \{0.01, 0.02, 0.03, 0.04, 0.05, 0.075, 0.1\}$.

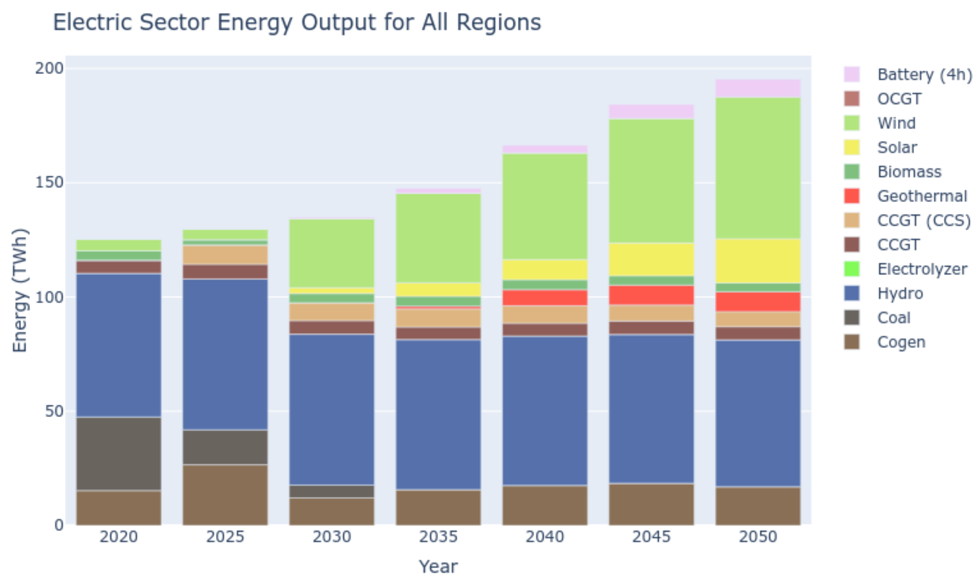
In evaluating all possible combinations of technologies and slack values, the model results deliver a variety of potential pathways to 100% electrification of the British Columbia road transportation fleet that highlight the range of roles certain technologies can play.

3 Results and analysis

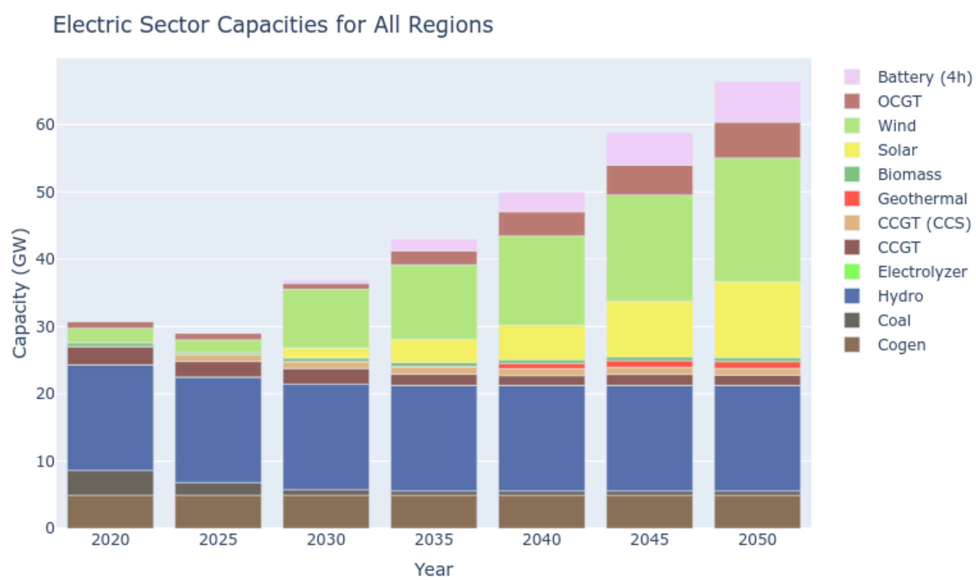
3.1 Optimal solutions

The combined electricity sector capacities and annual generation results for the base case are presented in Figure 3. The electricity sector experiences significant load growth mainly attributed to the electrification of British Columbia's road transportation fleet. The simultaneous increase in electricity demand and decrease in existing supply due to the early retirement of coal results in a need for significant new capacity. The model finds it optimal to meet the immediate need with roughly 1 GW of new CCGT-CCS capacity. Although overnight costs are considerably higher for the CCS option, the steep increase in the carbon prices results in CCS being the most affordable option when amortized over its lifetime. Beyond that, much of the increase in annual electricity demand is met by a combination of wind, solar, geothermal and biomass generation. Wind generation is most immediately competitive, with large capacity additions in 2030 while solar and battery storage systems are installed nearly in tandem.

The model concurrently solves a simplified hourly dispatch problem. Figure 4 displays the hourly electricity demand and generation for the 10 representative days in 2045.



(a)



(b)

Figure 3: Annual capacities and generation for the Alberta and British Columbia electricity sectors for the years 2020-2025.

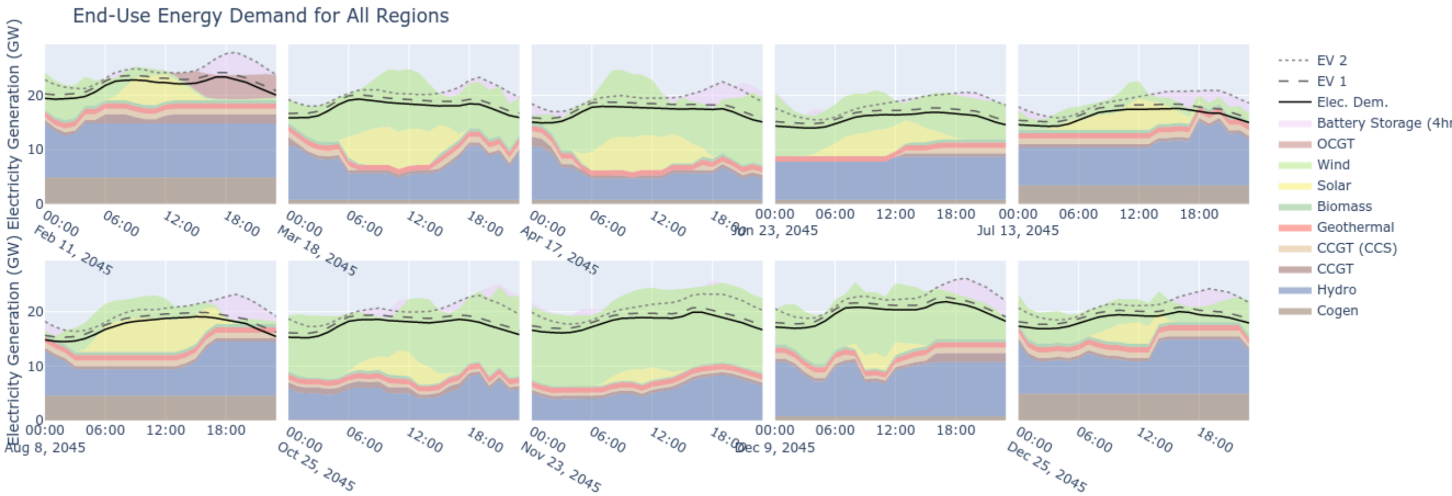


Figure 4: Hourly electricity generation for the 10 representative days in 2045.

From the results its clear that by 2045 that curtailment is a system feature. Although the hydro reservoirs are able to buffer much of the variability brought online by wind and solar generation, there are still hours in the year in which there is significant curtailment. This is attributed to the must run characteristics of variable renewables, ROR hydro and must-run hydro as well as the requirement for reservoir hydro to respect its annual energy budget.

February 11 represents the day in which the system's peak net load hour occurs. The poor evening wind and solar resource is compounded by high conventional electricity demand and evening charging of passenger electric vehicles. While the flexible hydro generators are able to dispatch to meet the evening peak, run-of-river hydro is running at a low capacity factor due to seasonal variations in flow. This culminates in the need for the system to dispatch peaking generators, namely four-hour battery storage and CCGT turbines. In fact, this is the only period in the year in which the CCGT plants are called upon.

3.2 MGA results

For illustrative purposes, the results of a single MGA instance are presented before analysing results of all instances en masse. The first instance considered is the case where the MGA objective function is to maximize the total solar generation over the entire model period while limiting system cost increases to 2% (i.e. $\epsilon = 0.02$).

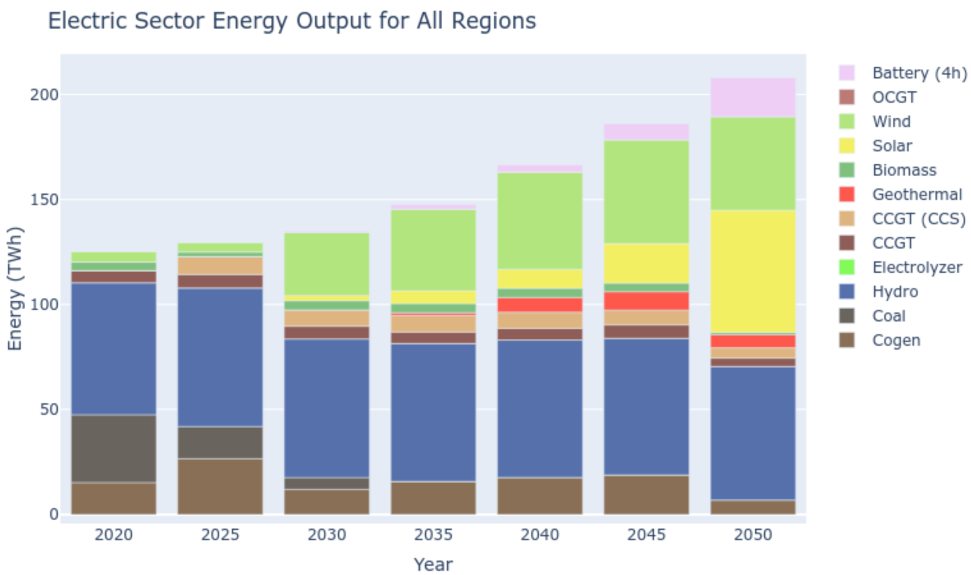
Figure 5 displays the energy and capacity plots for this case. In comparing these results to the base case, it's clear that most of the increase in solar PV capacity occurs later in the model years, particularly in 2050. The total generating capacity increases from 67 GW in the base case to over 100 GW in the MGA case. This is attributed to a number of dynamics, mainly solar PV substituting technologies with much higher capacity factors; system losses from increased use of battery storage; curtailment becoming a more predominant system feature; and solar PV contributing zero of its capacity to the reserve margin.

3.2.1 The near-optimal solution space

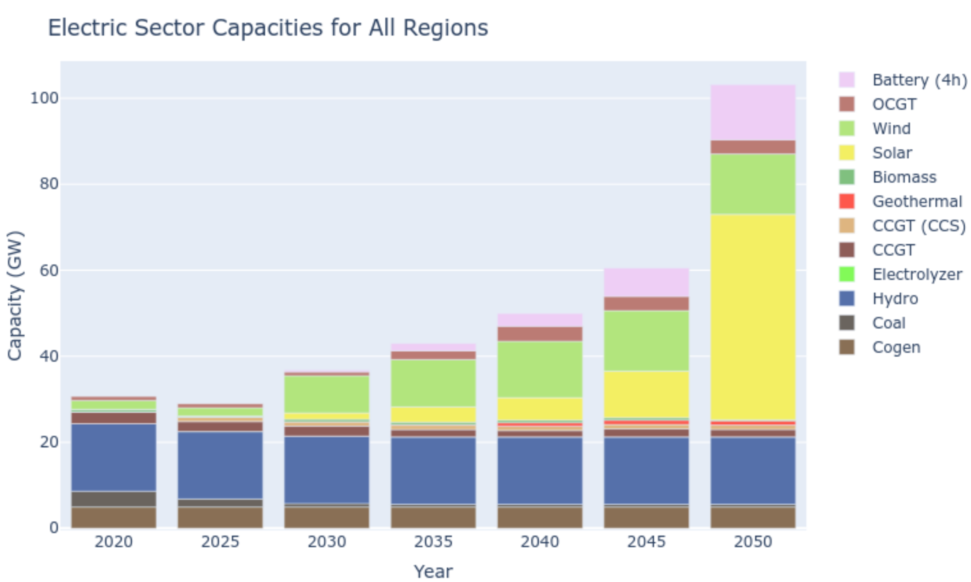
The original problem formulation has 654,077 decision variables which, in contrast to the illustrative case outlined in Section 2.1 with one variable, makes for a complex solution space. The approach taken in this paper, however, to minimize and maximize specific generator production levels allows for an analysis in prescribed planes or subspaces of the solution space.

Figure 6 displays the level of total generation for each technology group whose total generation is maximized and minimized as the MGA objective function. In the left most plot, it's apparent that in the optimal system configuration wind generation accounts for slightly more than 1 PWh of electricity over the model period. By setting a slack variable of $\epsilon = 0.01$ (i.e. allowing for a 1% increase to total system cost) and maximizing for total wind generation, the model is able to boost wind generation by a factor of nearly 40%. This steep increase tapers off as the slack values increase from 0.01 to 0.1. A similar trend is visible when minimizing total wind generation. At a 1% cost increase wind generation drops by a factor of 25%. Interestingly, wind generation is not forced out of the system at even a 10% cost premium.

In contrast to wind generation which is determined to be a system requirement, solar generation can be brought to zero at only a 2% cost premium. The same is true for



(a)



(b)

Figure 5: Annual capacities and generation for the Alberta and British Columbia electricity sectors for the years 2020-2025 under the MGA scenario of maximizing solar PV generation for $\epsilon = 0.02$

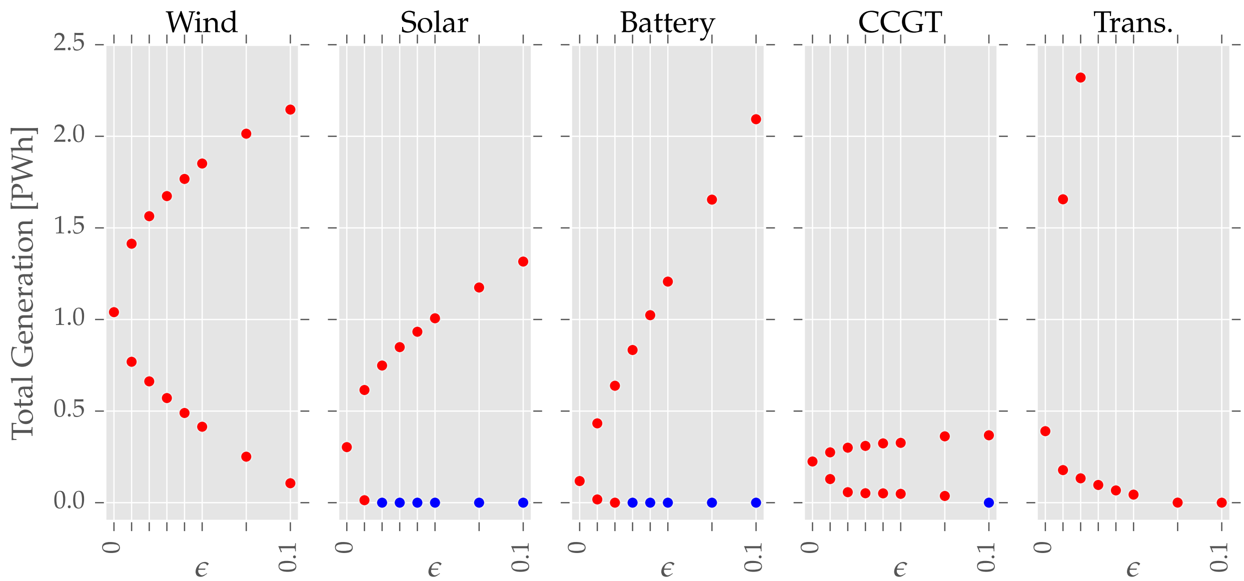


Figure 6: Near-optimal solution space for selected groups of technologies under different slack constraints.

battery use at a 3% premium. The tapering off of solar and wind generation under the maximization regime is indicative of the decreasing marginal value of variable renewables. Some of this, however, may be attributed to model artefacts such as limited resource sites and no integration with bordering electricity markets.

The near-optimal solution space for the CCGT activity is much more constrained than those of the other technology groups. In the maximization regime, its limited increase in generation is likely a response to it being the only generator in this figure to have substantial variable costs. Interestingly, even with Canada's steep carbon levy, CCGT[3] is found to exist in the system at even a 7.5% cost premium, which reflects the system's need for firm generation capacity.

Finally, the transmission technology is somewhat unique. The maximization regime in this case is non-nonsensical as the technology is used to effectively curtail electricity via losses[4]. The value of regional integration is made obvious in the minimization regime, however, as the intertie is still essential at even a 10% cost premium.

[3]recall that the CCGT group includes both CCGT and CCGT-CCS.

[4]the same is true to a lesser degree with battery storage

3.2.2 Correlations between technologies

Although Figure 6 gives an indication of the structure of the near-optimal solution space for certain technology groups by outlining their envelopes, the interdependence or substitutability of technologies is not yet clear. Intuitively, as the total generation from one technology is maximized or minimized, one would expect other technologies to respond appropriately.

Figure 7 displays the total energy generated per technology group as different groups are subjected to maximization (top row) and minimization (bottom row) under different slack values (columns). Hydro, coal and cogen generation are removed from the plots as their generation levels are relatively inflexible.

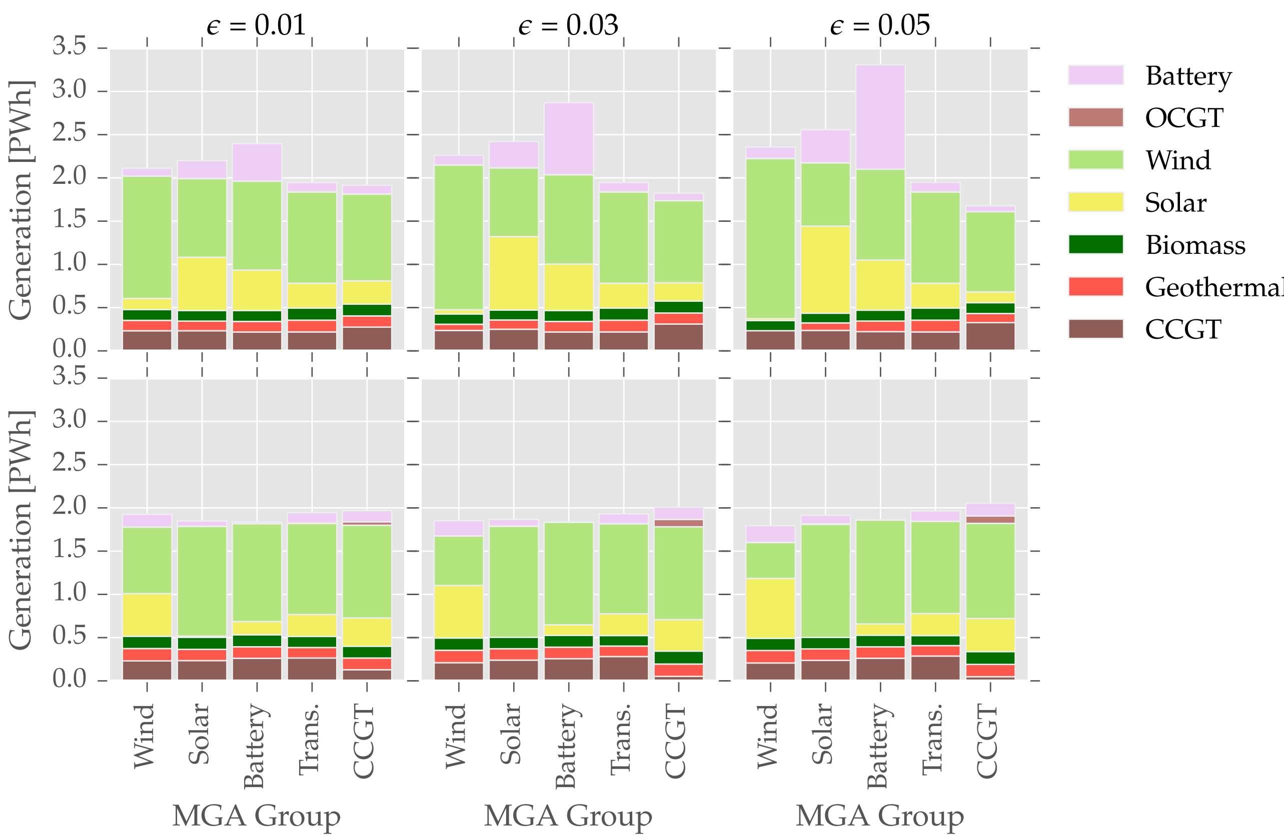


Figure 7: Breakdown of total generation as different technology groups are minimized/maximized with the MGA methodology.

It's clear that, for instance, when wind generation is being maximized, it is done to

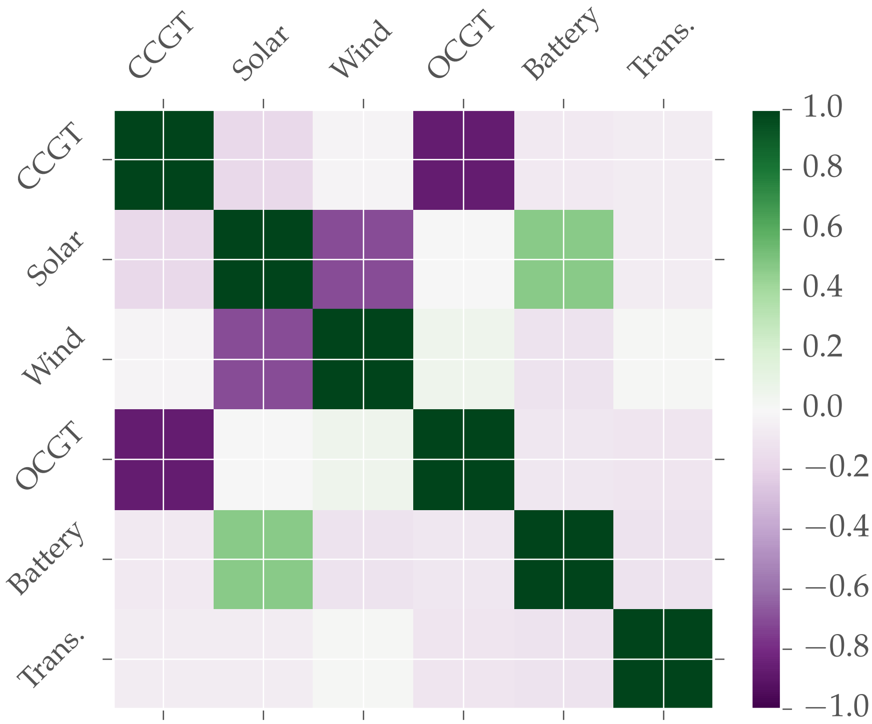


Figure 8: Correlation of total technology generation for all near-optimal solutions.

the detriment of solar PV generation. The same is true in reverse: when solar generation is maximized, a large decrease in wind generation is seen. Conversely, it is clear from Figure 7 that solar and battery generation move in lockstep – when one is maximized, there is a significant increase in generation of the other. This is consistent with intuition as the battery systems enable solar electricity to meet evening peaks.

An additional way of investigating the interrelations of different groups of technologies is by considering their correlations. For each of the MGA instances run, the correlations between the total generation of each technology group is displayed in Figure 8.

Negative correlations in Figure 8 imply substitute technologies. This is most clearly the case with the two gas generators — OCGT and CCGT — as they play similar roles in this model[5]. Wind and solar are similarly negatively correlated. That is, near-optimal solutions that see an increase in solar generation tend to see an overall decrease in wind

[5]detailed operational characteristics that differentiate OCGT and CCGT technologies are not included in this capacity expansion model.

generation, and vice versa. This is likely because there is a level of variability the system can economically accommodate.

Solar PV and batteries, by contrast, are found to be complimentary technologies. This is because the 2- and 4-hour battery energy storage allow solar-battery systems to meet evening peaks. By contrast, batteries and wind are found have a slight negative correlation. This indicates that longer duration storage is likely necessary to balance the intermittency of the wind resource. In the absence of long duration energy storage – such is the case in this model – transmission can be used for spatial smoothing of the resource, which is reflected by the slight positive correlation between wind and transmission technologies.

4 Discussion

4.1 What modelling gap does MGA fill?

Energy system optimization models have two sources of uncertainty: parametric uncertainty and structural uncertainty. Parametric uncertainty relates to unknowable parameters such as future prices or policy landscapes and can be effectively dealt with by techniques such as scenario analysis, sensitivity analysis and stochastic optimization. Structural uncertainties relate to the manifestations of the mathematical abstractions introduced into the model. MGA is a promising modelling technique to address such issues by effectively exploring the near-optimal solution space to uncover unexpected responses such as knife-edge solutions and penny switching. Moreover, as exhibited in the results of this project, MGA is also effective in contextualizing near-optimal solution spaces by quantifying the range in outcomes for specific technologies. That is, MGA techniques can be used to answer questions such as "How much more renewable generation could we bring online for an $x\%$ cost premium?".

Finally, MGA can be applied in situations where there is a binding constraint that limits the variety of model outputs/transition pathways, e.g. a hard fiscal or emission constraint. In such a case, MGA can be used to probe the near-optimal solution space for distinctive solutions while only being incrementally more ‘costly’.

4.2 Accessibility and transparency of the model

The authors intend to upload the model to a public github repository by the end of March 2021. The platform upon which it is based, Temoa, is fully open-source.

4.3 Usability for policy design

The Canadian energy system is in the beginning stages of what is sure to be a prolonged period of drastic growth, transformation, and integration. Many industry experts maintain that a promising path to energy system decarbonization is through electrification – i.e. the simultaneous decarbonization of the electric power system and electrification of many energy end uses, e.g. transportation. The physics of the electric power system make the political economy of electrification challenging: electrons obey Kirchoff’s law, not regional policies and interests. It is therefore crucial to have coordination between regional energy system planning authorities.

This project is designed with these challenges in mind. Its outcome is a tool that can aid in consensus building among energy system planning stakeholders. When presented a suite of near-optimal solutions that are similar in cost yet diverse in decision space (e.g. technologically and/or geographically diverse), stakeholders may find that a near-optimal solution is favourable to the optimal solution once their own preferences, values and concerns are brought to bear. What’s more, is that although different stakeholders may prefer different solutions, each of those solutions are generated from the same input scenario. This reminds those involved with the decision making process that there is a high degree of flexibility involved in the model solutions, and that a single scenario can appeal to stakeholders with differing views. This is especially relevant and useful in Canada’s federated energy system where stakeholders from different provinces may have a diverse set of values and interests.

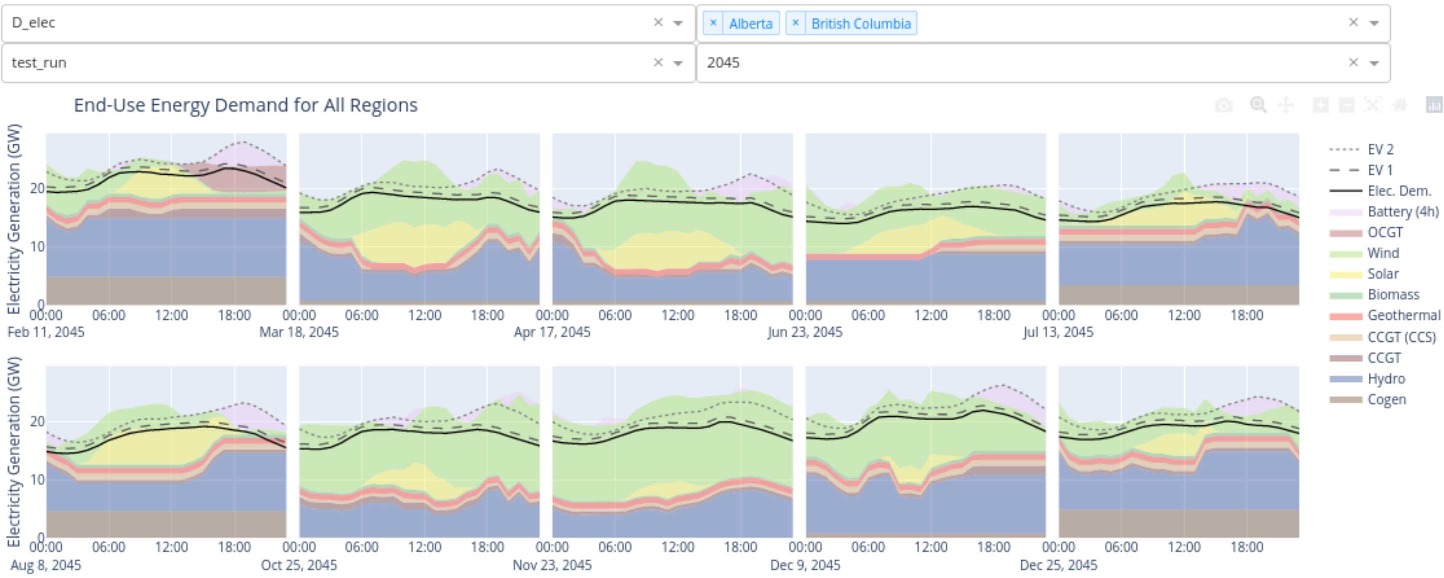


Figure 9: Screenshot of the current interactive dashboard to explore the suite of near-optimal solutions.

4.4 Benefits from being integrated in a national modelling platform

The MGA model introduced in this project is entirely separate from the energy system model to which it is applied. This is considered a feature as the technique (or model itself) is modular and can be applied to any energy system optimization model. That means that the MGA methodology to explore near-optimal solutions can be applied to the full gamut of models – from urban to continental scale, from production cost to capacity expansion, and from electricity system to transportation system models.

Even in the energy system planning model context it presents a unique tool to explore structural uncertainties and give stakeholders a portfolio of energy system transition pathways for a particular set of input assumptions.

4.5 Current state of development and proposed future work

The development of the optimization framework is complete. The current development is focussed on data vizualizations for capacity building exercises. Figure 9 displays a screenshot of an html applet used to interactively explore different near optimal solutions.

The ultimate objective is to further develop and refine methods that probe model uncertainties and subsequently translate them to energy system planning stakeholders. The future is highly uncertain, and we as modellers ought to do our best to communicate that with the tools we have available.

4.6 Data access issues

There are no data access issues identified.

5 Conclusion

This project introduced the modelling to generate alternatives methodology to explore the near-optimal solution space of energy system optimization models. These near-optimal solutions – similar in cost but diverse in technology portfolios – can give stakeholders involved with the energy system planning process a more diverse set of decarbonization pathways to evaluate. In fact, sub-optimal solutions may ultimately be preferred by decision makers once their own preferences, values and concerns are brought to bear.

The MGA methodology was applied to an energy system optimization model of Western Canada looking at the 100% electrification of British Columbia's road transportation fleet. Apart from the least-cost solution, a portfolio of near-optimal transition pathways are outlined to illustrate the variety of possible futures resulting from one set of input assumptions. Methodologies such as MGA to explore and communicate model uncertainties are considered an asset and a good tool to have in any modelling toolbox.

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