

Hedging the risk of increased emissions in long term energy planning



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ARTICLE INFO

Article history:

Received 8 August 2016

Received in revised form

27 January 2017

Accepted 6 February 2017

Keywords:

Risk

Uncertainty

Environmental impact

Energy modelling

Nuclear

ABSTRACT

The feasibility of meeting emission targets is often evaluated using long range planning optimization models in which the targets are incorporated into the system constraints. These models typically provide one 'optimal' solution that considers only a deterministic representative value of emissions for each technology and do not consider the risk of exceeding expected emissions for a given optimal solution. Since actual emissions for any given technology are uncertain, implementation of such an optimal solution carries inherent risk that emissions will exceed the given target. In this paper, we implement a stochastic risk structure into the OSeMOSYS optimization model to incorporate uncertainty related to the emissions of electricity generation technologies. For a given risk premium, defined as the additional amount that society is willing to pay to reduce the risk of exceeding the cost optimal system emissions, we determine the generation technology mix that has the lowest risk of exceeding this baseline. We focus on emissions risk since the literature on emissions risk is sparse while the literature on other risks such as policy risks, financial risks and technological risks is extensive.

We apply the model to a case study of a primarily fossil based jurisdiction and find that, when risk is incorporated, solar and wind technologies are built out seven and five years earlier respectively and that carbon free technologies such as coal with carbon capture and storage (CCS) become effective alternatives in the energy mix when compared to the 'optimal' solution without consideration of risk, though this does not include the risk of carbon leakage from CCS technologies. If nuclear is included as a generation option, we find that nuclear provides an effective risk hedge against exceeding emissions.

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1. Introduction

At the Conference of the Parties 21 (COP21), 195 countries affirmed their intentions to put in place measures to meet global emissions targets. The feasibility of meeting emission targets is often evaluated using long range planning models in which the targets are incorporated into the system constraints. This is typically done either by implementing a cap on CO₂ emissions [1–3] or by adding constraints, such as renewable energy portfolio standards, renewable energy credits or carbon taxes, that push the system to meet a given emissions target [3–6]. In all cases, an

'optimal' solution is found that meets the target at the lowest cost. Most of these studies do not incorporate uncertainty in the levels of emissions from the modelled technologies. As a result, the risk of exceeding the emissions target is not quantified, leaving a gap in the literature as discussed in section 2.1. There are a number of methods that have been used to incorporate uncertainty into long term energy planning models, as discussed in detail in section 2.3.

In this study we apply a stochastic risk enabled version of the Open Source Energy Modelling System (OSeMOSYS) [7,8] to the Alberta, Canada electricity system. The Alberta system is fossil fuel based, similar to many US states and countries such as China and India, making our results more broadly applicable than those Parkinson and Djilali obtained for a hydro based jurisdiction. In addition, we consider how nuclear, a low carbon technology that is often ignored due to political and social considerations, impacts the emissions risk for the Alberta, Canada electricity system.

The stochastic risk enabled version of OSeMOSYS is developed using the stochastic risk framework described by Krey and Riahi [9]

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Nomenclature

a_{ij}	Performance parameters of technologies in the model.
b_i	Limits on installed capacity and operating parameters.
c_j	Vector of all cost parameters considered by the model.
$C(x_j)$	Total cost of system for a given decision vector, x_j .
$C(x_j^*)$	Total minimum cost of the system as determined by deterministic optimization method.
\bar{r}_j	Mean, or expected, value of the uncertain parameter.
$r_j(\omega_n)$	Random sample of the uncertain parameter.
f	Risk premium. The extra amount that society is willing to pay to minimize risk.
$F(x_j)$	Sum of the system cost, $C(x_j)$, and weighted risk.
x_j	Vector of installed capacities and operating parameters.
x_j^*	Optimal (lowest cost) decision vector as identified by deterministic optimization method.
N	Number of samples to consider when determining the risk vector.
R_{max}	The maximum risk allowable.
$R(x_j, \omega_n)$	Risk for a given decision, x_j , for a single random draw from the probability space, ω_n .
$R(x_j)$	Total risk for a given decision vector, x_j .
ρ_r	Risk aversion parameter. Used to convert risk into an equivalent cost.

and adapted by Parkinson and Djilali [10]. We use this framework to incorporate uncertainty in environmental performance of technologies into OSeMOSYS and assess the risk that emission targets will be exceeded. While Parkinson and Djilali use a custom linear programming model to apply the risk framework we implement this framework in OSeMOSYS. We use OSeMOSYS as it is a widely used energy system model that is open source and, by using this model, we contribute to the code base available for modellers using OSeMOSYS.

Although this study focuses on climate impact emissions risk, there are many other environmental impact risks posed by energy technologies that could be included in a risk framework including air pollution, water use and/or contamination, waste stewardship, wildlife impacts and land use. This study focuses on climate change emissions risk as this is an area that has not been thoroughly studied, as discussed in our literature review, and which has a global impact.

2. Literature review

Uncertainty is of concern in energy planning because uncertainty creates risk. Uncertain parameters in energy planning include: capital cost of generation technologies; operation and maintenance costs; fuel prices; availability of imported fuels; construction schedules for new plants; demand projections; and uncertainty in the emissions of a given generation technology or generation mix [11–15]. These uncertainties are compounded by the uncertainty of projecting over decadal time frames, as is typical in energy system planning. Quantifying the risk associated with these uncertain parameters requires an understanding of both the methods available for addressing risk in models, as discussed in

section 2.3, and of the sources of uncertainty as discussed in section 2.1. One rarely considered source of uncertainty is environmental performance risk, defined as the risk that a given technology's environmental impact is greater than the expected impact. We discuss this in section 2.2.

2.1. Sources of uncertainty

As in all modelling, there are many sources of uncertainty in energy system modelling. These include financial uncertainty, resource availability, sensitivity of the climate system to emissions and uncertainty in climate policies as well as uncertainty in future demand for energy services. There has been significant work in each of these areas.

Szolgayová et al. [16] use a portfolio analysis approach to investigate financial uncertainties in a model that considers a simplified set of four technology options. Hunter et al. [17] extend the modelling tool TEMOA to include cost uncertainty. Other examples of models using portfolio analysis methods to consider financial risks include work done by Krey et al. [18], Usher and Strachan [19], Messner et al. [20], Webster et al. [21], Leibowicz [22] and Arnesano et al. [23]. Each of these papers considered the financial risks associated with future energy prices, carbon policies and/or social costs and determined an energy system buildout that hedged the risk of financial losses in the system. Wu and Huang [24] consider the potential for zero marginal cost technologies such as wind and solar to hedge against fossil fuel price risk using a similar method.

Variability in resource availability is a significant source of system uncertainty, both in terms of the ability of renewable resources to meet demand in the short term and in terms of resource constraints on generators in the longer term. Stoyan and Dessouky [25] use a mixed integer programming approach to evaluate various scenarios of resource availability to enhance system planning. Tan [26] provides a method for incorporating inoperability risks into a linear programming model in which the resource mix is optimised to reduce the risk that demand is not met when energy sources become inoperable due to supply constraints. Martinez-Mares and Fuerte-Esquivel [27] use a robust optimization approach to consider the impact of wind resource variability on the optimal system. Each of these three studies is based on a stochastic evaluation of the cost of this variability.

Studies by Loulou et al. [28], Ekholm [29] and Syri et al. [30] investigate uncertainty due to variability in the sensitivity of climate to carbon emissions, and calculate the costs associated with meeting specified climate change temperature targets. Each of these studies use a stochastic programming model to determine the financially optimal system given this uncertainty in climate sensitivity.

Uncertainties in climate policy also create risks for investors and a number of studies have investigated how decision makers will react to these risks [31–33]. These studies find that uncertainty in policy can undermine the potential benefits of a policy, in particular when policy decisions are short-term or if policy makers do not consider the potential reaction of investors.

There are also a number of studies that consider a combination of uncertainties. Most of these studies combine cost uncertainty with policy uncertainty and evaluate the financial risk associated with these uncertainties [34–44], either with stochastic programming or interval programming.

However, none of these studies considers uncertainty related to the environmental performance of energy technologies in fossil based jurisdictions nor do any of these studies consider nuclear. This is summarized in Table 1. It is important to fill this gap in the literature since ignoring this uncertainty could lead to systems with

higher than predicted emissions, meaning jurisdictions could miss their emissions targets.

2.2. Environmental performance uncertainty

As outlined above, few studies consider uncertain environmental performance of alternative energy system realizations. In this paper we define environmental performance uncertainty as the uncertainty in the environmental impact of a given technology. This could be due to variability in pollutant emissions such as carbon dioxide, uncertainty in the amount of water use, uncertainty about the impact of construction to name a few.

There are a small number of studies in the literature that address environmental performance risk. Parkinson and Djilali [10] investigate the impact of uncertain environmental performance of energy technologies, as defined by their carbon dioxide emissions, on the potential of these technologies to hedge against climate impact risk in British Columbia, Canada, using a stochastic programming approach. Li et al. [45] use a combined fuzzy and stochastic approach to consider uncertain environmental performance, again as defined by greenhouse gas emissions, in combination with other uncertainties, to reduce the risk that a generic energy system would fail to meet specified emission targets. Heinrich et al. [46] use a multi-objective optimization technique to investigate how uncertain technological parameters in their model influence environmental impact risks for the South African energy system. They specifically consider the uncertainty in emissions from power plants for each technology as well as the efficiency of each technology and include these in their multi-objective optimization model. Kanudia et al. [47] use a multi-scenario framework to evaluate the impact of uncertainty in future policy on the overall climate impact of the energy system in Quebec, Canada.

2.3. Risk methods in energy system models

Ascough et al. [48] provide an overview of different methods of addressing risk in energy-economic models. Krey and Riahi [9] note that most of these approaches are for 'stylized models' that lack an explicit technology representation as defined as the ability to model the efficiency and operating parameters of a specific technology. Examples of models that include technology-explicit representations include multi-objective optimization [46], near optimal techniques [49,50], monte-carlo simulation [51] and stochastic optimization methods originally developed for financial portfolio analysis [9].

Incorporating risk in a multi-objective optimization model requires defining objectives for the model that are expected to reduce the perceived risk. The multi-objective optimization then determines a set of possible decisions that meet these policy objectives. Near optimal techniques, including model generated alternatives (MGA), do not explicitly take into consideration risk and uncertainty, but allow for the policy decision maker to choose from amongst a number of near optimal options that are all unique. These unique solutions allow the decision maker to choose which of the near optimal solutions meets non-specified constraints or

objectives of the decision maker. Neither multi-objective optimization and near optimal techniques take uncertainty and risk into consideration endogenously therefore this method was not chosen for this study.

Monte-Carlo simulation techniques do allow the modeller to take risk into consideration endogenously, similar to financial portfolio risk methods. However, Monte-Carlo methods find an optimal solution to large number of random problems but do not guarantee that all of these solutions are feasible and can be implemented. This approach is useful for many energy system modelling questions but is not directly applicable to the consideration of increased risk of emissions.

Portfolio analysis uses a stochastic approach to develop expected distributions for the future value of the potential investments. A risk model is then used to choose an investment portfolio that balances the financial risk of this uncertainty with the initial cost of the investment. When applied to energy systems modelling, this approach considers the uncertainty in the cost of future energy supply rather than the uncertainty in future value of investments. Krey and Riahi [9] demonstrate that the risk methods applied to portfolio analysis can be incorporated into energy-economic models. They provide three alternative formulations of a risk-based stochastic linear programming problem and show that these formulations are numerically equivalent. Parkinson and Djilali [10] argue that, for policy decisions, the formulation that minimizes risk for a given risk premium provides the greatest benefit to the policy maker by providing a direct link between the risk and the cost of a policy decision. The risk premium is a factor that indicates the additional cost that society is willing to pay to reduce the exposure to risk. Parkinson and Djilali adapt the financial risk structure to the quantification of environmental performance risk and, more specifically, the risk of increased carbon dioxide emissions. As this method has already been applied to the risk of increased carbon dioxide emissions it fits well with the purpose of this study.

Based on this review of the literature, we find that financial portfolio analysis, as presented by Krey and Riahi [9], provides an effective method for addressing risk in energy systems models. It allows the modeller to quantify risks in the model structure and determine generation portfolio decisions that hedge against these risks endogenously. Furthermore, although many authors have investigated cost and other uncertainties, little work has been done to quantify the risk of excess emissions. Parkinson and Djilali [10] adapt the financial portfolio analysis methodology to address the risk of excess emissions. In this study, we extend the work of Parkinson and Djilali by implementing the method they use in the OSeMOSYS Open Source Energy Modelling System, making it available to anyone wishing to consider risk in energy systems modelling. We apply the methods to a case study of the electricity system in Alberta, Canada to investigate strategies by which the risk of excess emissions can be reduced. While Parkinson and Djilali focus on British Columbia, Canada, a jurisdiction with large hydro resources, we look at Alberta, Canada, a jurisdiction that has predominantly fossil generation in the energy mix that is similar to many US states and countries such as China and India. In addition,

Table 1
Uncertainty studies in the literature.

Uncertainty considered	Hydro based jurisdiction	Fossil based jurisdiction	Consideration of nuclear
Financial	Yes [21]	Yes [16–24]	Yes [22]
Resource availability	Yes [26]	Yes [25–27]	No
Climate sensitivity	Yes [28,30]	Yes [28–30]	No
Climate policy	No	Yes [31–33]	Yes [31]
Emissions levels	Yes [10]	This study	This study

we expand the analysis to consider the risk mitigation potential of nuclear energy and investigate how that impacts both risk and cost.

3. Methodology

We implement a techno-economic linear programming model to investigate uncertainty and risk hedging strategies and technologies following on the work by Krey and Riahi [9] and Parkinson and Djilali [10]. Such models are based on the generic linear programming problem formulation:

$$\text{Min } C(x_j) = \sum_j (c_j x_j) \quad (1)$$

$$\text{s.t. } \sum_j (a_{ij} x_j) \leq b_i \forall i \quad (2)$$

$$x_j \geq 0 \forall j \quad (3)$$

The objective of the problem, as defined in Equation (1), is to find the solution vector, x_j , that minimizes the sum of $c_j x_j$, where j represents the set of all possible decisions. In energy systems models, c_j , the vector comprising the cost parameters, is often separated into capital, fixed and operating costs while x_j , the vector comprising the decision variables, is often separated into new capacity and operating decision vectors. The subscript j then represents new capacity and operating decisions for each technology in the model. The performance parameters for the technologies are a_{ij} and the activity or installed capacities are restricted by b_i as shown in Equation (2).

This general formulation has been implemented in a number of techno-economic energy system modelling tools, including MESSAGE [52,53], Times/MARKAL [54] and, more recently, the Open Source Energy Modelling System (OSeMOSYS) [7,8].

The optimal deterministic system cost, $C(x_j^*)$ is defined as the total minimized system cost, as determined by Equation (1), for the system realization, x_j^* , with no consideration of risk. A risk measure, $R(x_j)$ is then introduced that represents the total risk that a given decision vector, x_j , will result in higher total cost than, $C(x_j^*)$. Three different approaches to incorporate risk into linear programming models are described by Krey and Riahi [9]:

- Minimize the weighted sum, $F(x_j)$, of the total system cost and the risk measure. This is the approach implemented in MESSAGE by Messner [20] and discussed by Dantzig [55]. A *risk aversion factor*, ρ_r , is introduced that, when multiplied by the risk, $R(x_j)$, of the solution vector converts the risk into an equivalent cost, as shown in Equation (4).

$$\text{min} F(x_j) = C(x_j) + \rho_r R(x_j) \quad (4)$$

- Minimize the risk measure subject to a maximum expected total system cost. In this case, a *risk premium*, f , is introduced that represents the extra amount that society is willing to pay, above the optimal deterministic system cost, $C(x_j^*)$, to reduce risk below that which is associated with the optimal deterministic solution.

$$\text{min} R(x_j) \text{ s.t. } C(x_j) \leq (1 + f) C(x_j^*) \quad (5)$$

- Minimize the total system cost unssder constrained risk. In this case, the cost of the system is minimized subject to a maximum acceptable level of risk, R_{\max} .

$$\text{min} C(x_j) \text{ s.t. } R(x_j) \leq R_{\max} \quad (6)$$

All three approaches use a risk parameterization that is stochastically determined by successive draws from the probability space, as discussed by Hazell [56]. Hazell's approach is based on cost uncertainty, where the total absolute deviation of cost for a single draw, from the expected value for each set of draws, is used to measure the financial risk of the solution associated with that draw.

Krey and Riahi show that these three approaches are numerically equivalent in that one can choose a *risk aversion factor*, a *risk premium* or a limit on the level of risk which will result in the same decision vector. For financial risk, the risk measure and the cost parameter in the model are both monetary, so the structure with the *risk aversion factor* provides insights for financial decisions. For energy systems analysis, where the risk measure may correspond to non-monetary risks, the structure with the *risk premium* allows for a clear connection between the reduction of a given risk and the monetary cost. Parkinson and Djilali [10] observe that the *risk premium* can be considered the cost of hedging to reduce risk. The third structure, where cost is minimized for a given level of risk, allows the modeller to obtain marginal costs from the model which is not possible with the first two formulations, but does not allow for a direct link between increased costs and reduced risk [9]. As we are interested in the increased cost to mitigate climate impact risk, we utilize the *risk premium* structure to obtain insights into climate impact risks.

To incorporate the *risk premium* model structure into a linear programming model, Krey and Riahi provide a risk metric, the “*upper mean absolute deviation*”, as defined in Equations (7) and (8). Equation (7) provides a measure of the risk for a given decision vector, x_j , for one random draw from the probability distributions of the performance variable, $r_j(\omega_n)$ for each element in the decision vector. This risk measure is then summed, in Equation (8), to give the risk based on N random draws from the probability distributions of each performance variable. This overall risk, as given by Equation (8), corresponds, for financial risk, to the expected underestimation of the system cost [20]. For our purposes, this can be considered as the expected underestimation of the system emissions of the deterministic model, which we term, “*risk*”, in the remainder of this paper.

$$R(x_j, \omega_n) = \max \left\{ 0, \sum_j [r_j(\omega_n) - \bar{r}_j] x_j \right\} \quad (7)$$

$$R(x_j) = \frac{1}{N} \sum_n R(x_j, \omega_n) \quad (8)$$

When applied to the risk of increased carbon dioxide emissions, as we do in this paper, \bar{r}_j is the vector of average values of carbon dioxide emissions for each technology and $r_j(\omega_n)$ is the vector of random draws from the probability distribution of carbon dioxide emissions for each technology. The difference between these two parameters is multiplied by the decision vector, x_j , to find the risk for that decision vector and random draw. Equation (8) gives the risk based on N random draws from the probability distributions of the emissions of each generation technology. A sufficient number of random draws must be taken to ensure convergence of the model while keeping it to a minimum to reduce computation time.

As discussed earlier, the decision vector, x_j , for most energy system models is comprised of new capacity and operating decisions. Here, we consider only the portion of the decision vector, x_j , which corresponds to the operation decisions. \bar{r}_j is then the vector

of average lifecycle emissions per unit of generation for each technology while $r_j(\omega_n)$ is the vector of predicted lifecycle emissions per unit of generation for a technology for random draw n .

For each random draw, n , we sum only the downside risk (i.e. the chance that the emissions are higher than expected) to obtain, $R(x_j, \omega_n)$, the risk of emissions exceeding the expected level. The risk for each of the random draws are then summed to find the risk based on N random draws, $R(x_j)$. A single optimization is then performed to minimize this risk.

For the linear programming GNU MathProg code, as implemented in OSeMOSYS, please refer to [Appendix A](#).

4. Case study -methods

The risk framework described above is incorporated into the Open Source Energy Modelling System (OSeMOSYS) [7,8]. We then implement into this risk-enabled version of OSeMOSYS, a model of the electrical energy system for Alberta, Canada. The Alberta model was originally developed in OSeMOSYS by Lyseng et al. [57] and was recently updated to include policy announcements made by the Alberta government in late 2015 [58,59]. This section provides a brief description of the general model structure. For those parameters not described here please refer to Lyseng et al. [57].

[Fig. 1](#) shows the general structure of the Alberta model, with generators that contribute to the reserve margin shown on the left. The reserve margin ensures that there is enough dispatchable generation in the generation mix to meet the demand for times when non-dispatchable generation such as wind and solar are not available. It is also used to ensure the system has energy available to meet projected peak loads since the time slice structure for long term optimization averages out some of these peaks.

The generation options that contribute to the energy mix in Alberta include coal fired generation (COAL), natural gas fired combined cycle turbines (CCGT), simple cycle natural gas fired turbines (SCGT), and natural gas fired cogeneration with heat production plants for industrial loads (COGEN). Carbon capture and sequestration (CCS) can be implemented on either a CCGT natural gas plant or a coal plant and is implemented as two additional technologies available in the model. Generator performance and cost data are taken from the U.S. Energy Information Agency [60] while capacity limits are based on data from the Alberta Electric System Operator (AESO) [61]. Biomass is limited in the amount of energy available each year while the other forms of generation are limited in terms of maximum installed capacity.

Nuclear is currently not considered a generation option by the Alberta Electric System Operator (AESO), as outlined in their long term plan [61]. Accordingly, a first set of model runs was performed without nuclear as a generation option. A second set of model runs with nuclear enabled was then performed to compare the risk profiles with and without nuclear.

The current Alberta system is reliant on coal and natural gas

with smaller amounts of wind and hydro making up the balance. The natural gas in Alberta is split between cogeneration providing heat and power to industry and conventional natural gas generators, both simple cycle and combined cycle, meeting much of the remaining load. The model structure implemented by Lyseng et al. is a lumped system model, with no consideration of transmission which follows from the Alberta Electric System Operator (AESO) mandate to, “plan for a transmission system that is free of constraints” [62]. We optimize over the period 2010 through 2060 using a high-demand, average-demand and low-demand time slice for each season based on the AESO demand growth forecast [61]. Each season is three months long, for a total of 12 time slices per year. The size of the time slices varies from 283 h for the shortest peak time slice to 1201 h for the longest off peak time slice.

In fall 2015, Alberta made the announcement that existing coal generation will be retired and that 30% of all generation will be from renewable sources by 2030 [59]. A \$30/tCO₂ carbon tax will be implemented and will be used to fund incentives for renewable sources. The carbon tax will apply to any emissions from a generator that exceeds the level of emissions of a theoretical best in class, high efficiency natural gas plant, expected to be 0.4 tCO₂/MWh in 2018, decreasing to 0.3 tCO₂/MWh in 2030.

We implement this policy by eliminating residual coal capacity in 2030 and applying the \$30 carbon tax on emissions above the best in class standard, starting in 2018 at 0.4 tCO₂/MWh and decreasing linearly to 0.3 tCO₂/MWh in 2030. With these policies in place, we increase the renewable energy credit (REC) until the 30% generation level is met. Lyseng et al. [58] found that a REC of \$25/MWh was sufficient to obtain 30% generation from renewable sources by 2040 and we, therefore, implement a \$25/MWh REC in this study. Although there is no specified overall emissions limit applied, there are emissions targets implied by these policies. Our model similarly does not apply a specific emissions limit on the system but determines the level of emissions with these policies in place.

Distributions of the emission intensities were created based on the review of lifecycle emissions performed by the IPCC [63, Annex II], as shown in [Fig. 2](#). Lognormal distributions were fit to the percentiles published by the IPCC following the work by Parkinson and Djilali [10]. For each random draw, n , we obtain the predicted lifecycle emissions per unit of generation for each technology from these distributions.

Three technologies shown in [Fig. 2](#) require elaboration. First, the emissions from solar are based on the IPCC study findings for Solar Photovoltaic (PV) rather than Concentrated Solar Power (CSP). This is consistent with the expectations that Alberta will have distributed PV rather than CSP. Neither the Alberta Electric System Operator (AESO) nor the Canadian Solar Energy Industries Association mention CSP in their plans for the foreseeable future, while both mention Solar PV as a viable technology [61,64].

The IPCC study provides only a single emissions distribution for each of coal and natural gas, although there are multiple generating technologies for each of these fuels. We assume that the IPCC figures are for the worst generator using a given fuel, namely existing coal plants and typical SCGT plants. Emissions from other plants that use the same fuel are scaled down based on their relative conversion efficiency.

Data for carbon capture and storage (CCS) provided by the IPCC is sparse since there are few systems in operation to quantify the emissions. The IPCC provides simply a minimum and maximum value for these technologies rather than a distribution. We assume that the distribution of emissions from plants with CCS follow a similar shape as for those without CCS. We linearly scale the distribution for plants with CCS such that the minimum of the resulting distribution matches the minimum provided by the IPCC for plants with CCS.

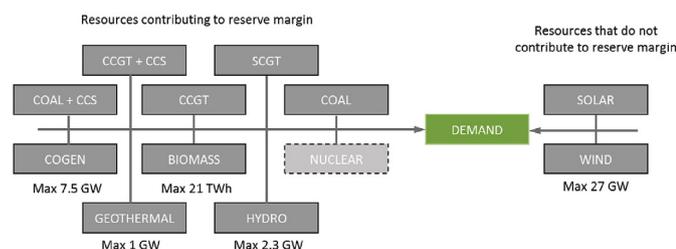


Fig. 1. Diagram of generation options in the modelled Alberta system. Generators on the left contribute to the reserve margin. Generators on the right (i.e. wind and solar) do not.

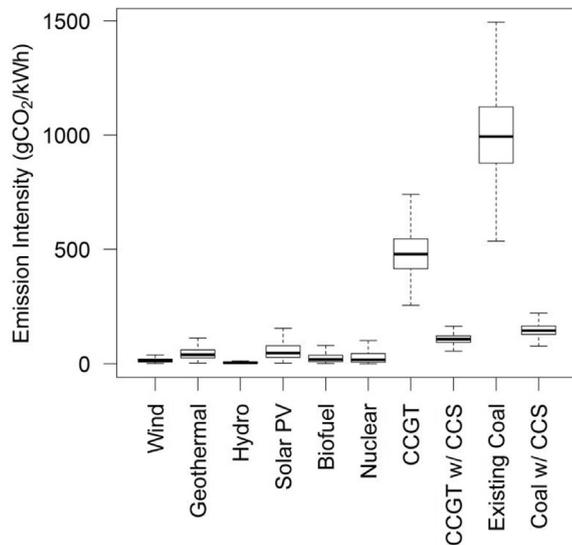


Fig. 2. Distribution of emission intensity for various generation technologies (after [10]) The boxes show the 25th to 75th percentiles while the whiskers show the 95% probability limits of the lognormal distribution.

5. Case study-results

As noted above, two sets of analyses were performed. First, following the Alberta Electric System Operator projections, we consider the case without nuclear as a generation option. We then allow nuclear as a generation option and compare the results. In both cases, we constrain our model to meet the newly announced Alberta policies discussed earlier.

5.1. System without nuclear

The analysis is first performed without implementation of the risk framework. Fig. 3 shows the resulting installed capacity for each technology, over time, as a stacked area plot.

As shown in this figure, coal is mostly pushed out of the system in 2020 by CCGT with only a small amount of residual coal capacity lasting until 2030. Due to reserve margin requirements, SCGT is installed as backup for the large amounts of renewable generation being installed. A large build out of wind begins in the year 2019, with solar entering the generation mix in 2050.

When a 5% risk premium is applied, there is a clear shift in generation technologies, as shown in Fig. 4. The build out of wind starts four years earlier, and the build out of solar starts eight years earlier. Co-generation expands slowly in the first 20 years, then remains flat until approximately 2040, when it starts to be slowly reduced due to coal with CCS entering the system, eliminating CCGT entirely.

Fig. 5 shows the installed capacity in the year 2050 for each of the modelled risk premiums. The increase in solar capacity is clearly seen – each increase in risk premium causes a clear increase in the amount of solar installed. Also notable in this figure is that small increases in risk premium cause coal with CCS to become more attractive while combined cycle natural gas and co-generation become less attractive. The use of SCGT to meet the reserve margin is less prevalent at higher risk premiums due to installation of coal with CCS.

The large amount of SCGT capacity installed by the model is rarely used for generation, as shown in Fig. 6. It is installed to ensure that generation for peak periods is always available even when variable resources such as wind or solar are unavailable. It is

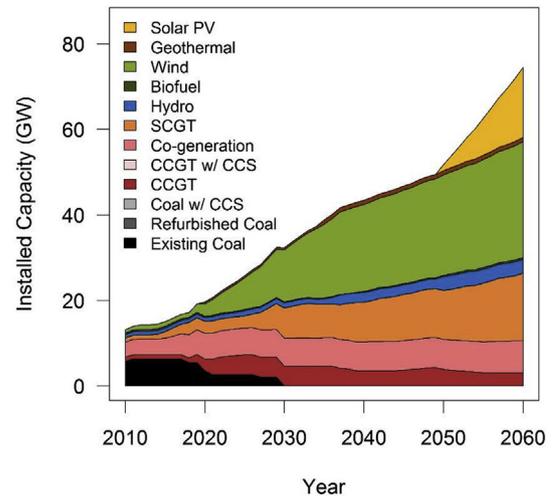


Fig. 3. Installed generation capacity over time for system with no consideration of risk.

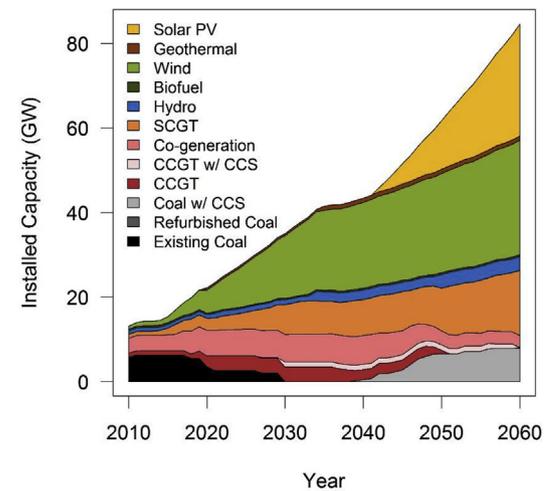


Fig. 4. Installed generation capacity over time for system with 5% risk premium.

important to highlight that our model lacks the short time-scale resolution to show the operational characteristics for short term peak generators but does include the requirement to install peaking generation. Other than the clear absence of any generation by SCGT, as shown in Fig. 6, the operational capacity factor for each generator remains approximately the same for each risk premium level.

As the risk premium increases, the amount of potentially asynchronous generation such as PV and Wind in the system increases to nearly 50% of the total generation. We expect that, if there was such a large build out of wind and PV in Alberta, that many of the wind turbines installed would be installed with synchronous generators as this is both technically feasible and done in some existing wind turbine installations [65]. In addition, PV installations could be connected to the grid with synchronous inverters, further mitigating this impact. Finally, the SCGT installations, though not used for significant generation, would likely be called upon for grid balancing duties which should allow for grid stability even with such a large amount of wind and PV generation.

The current risk framework considers only the risk associated with generation emissions, and not the risk associated with construction emissions. Given the large quantity of new construction

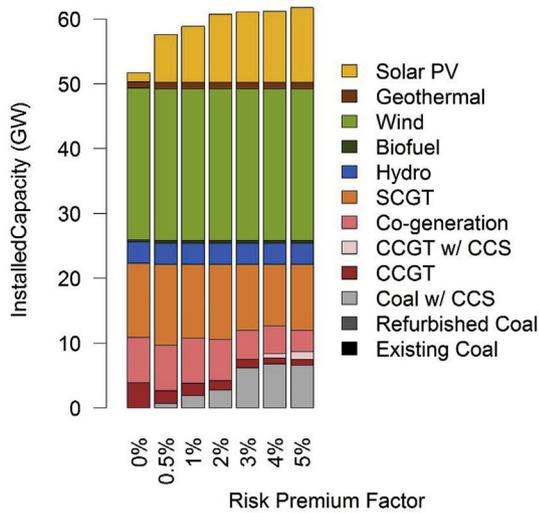


Fig. 5. Installed capacity by technology at various levels of risk premium in the year 2050.

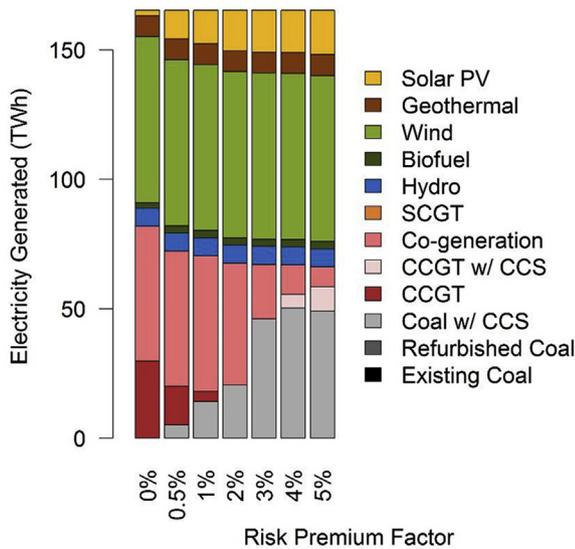


Fig. 6. Generation by technology at various levels of risk premium in the year 2050.

predicted by the model, these emissions and their associated risk may be significant. In addition, our model does not quantify all of the uncertainty related to the technical potential of carbon capture technologies nor the long term stability of the stored carbon.

The Alberta average load in 2050 is under 19 GW, with a peak near 30 GW, whereas the total installed capacity in 2050 varies from approximately 55 GW for the base model to over 60 GW for the 5% risk premium. This apparent over-building results from the requirement for dispatchable generation to meet the reserve margin combined with the lower risk of carbon dioxide emissions from wind and solar. To reduce the emissions risk, more solar is installed, but the same level of dispatchable generation is installed to ensure system reliability.

Fig. 7 shows the distribution of realized emissions for each of the risk premiums simulated, showing a clear trend of reduced emissions with increased risk premium. The distribution of emissions is compressed at higher risk premium indicating a reduced risk of exceeding expected emissions.

5.2. Nuclear available as a generation option

Fig. 8 shows the installed capacity for each technology on a stacked area graph with no consideration of risk, but with nuclear enabled.

When compared with Fig. 3, the major change with nuclear available is the absence of solar generation from the mix. Other notable changes include the reduction of SCGT buildout after 2040 which is replaced by nuclear capacity and the complete elimination of CCGT capacity by 2055.

When a 5% risk premium is applied, there is a significant shift in the generation mix, as shown in Fig. 9, relative to the model with no consideration of risk. Wind comes on line approximately five years earlier while nuclear replaces cogeneration and coal entirely. The additional nuclear is installed as nuclear has very low emissions and very low variability in terms of the predicted emissions. This means it is a cost effective risk hedge for the model to choose. Additional SCGT is installed to meet the reserve margin.

Fig. 10 shows the installed capacity in 2050 for each of the risk premiums considered. In the existing AESO projections case, where nuclear is unavailable, the installation of solar increases steadily with the risk premium, as shown in Fig. 5. When nuclear is available, solar is installed in 2050 and only when the risk premium rises to 4%.

Fig. 10 shows that the generation mix changes little with increases in the risk premium over 1%. The generation mix, once coal and natural gas are pushed out, remains largely nuclear and wind, with SCGT meeting the reserve margin. Small amounts of other technologies comprise the remaining generation mix.

In comparison to the case where nuclear is not available in the model, the total installed capacity for the system is quite different with nuclear available. As shown in Fig. 5, the 2050 installed capacity rises from 55 GW for the base model to over 60 GW for the 5% risk premium under the current no nuclear policy. When nuclear is available the total amount of generation is reduced to around 50 GW, and an increase is seen only when the risk premium rises to 5%. With nuclear available it is more sensible to use nuclear to replace natural gas generation up to a 4% risk premium rather than installing more wind and/or solar. Since nuclear meets the system reserve margin, it can replace natural gas rather than adding to the installed capacity of the system.

As is the case without nuclear in the mix, when nuclear is

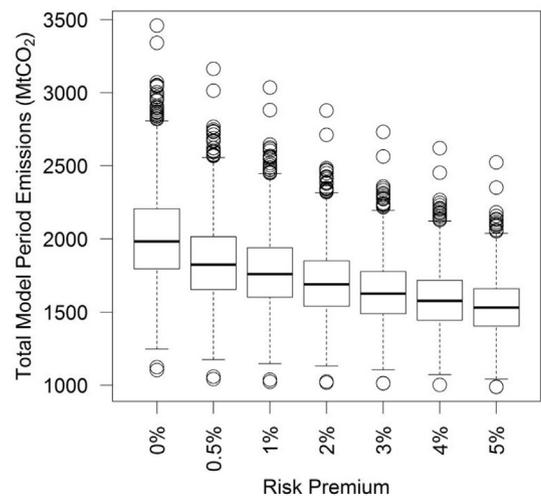


Fig. 7. Total model period emissions for each random realization at various levels of risk premium.

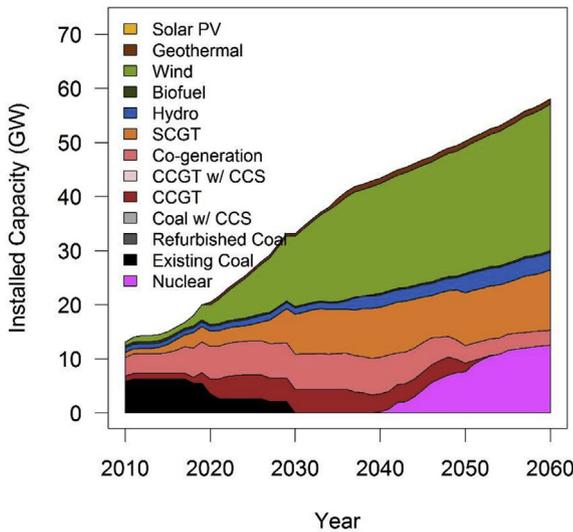


Fig. 8. Installed generation capacity over time for system with no consideration of risk and nuclear as a generation option.

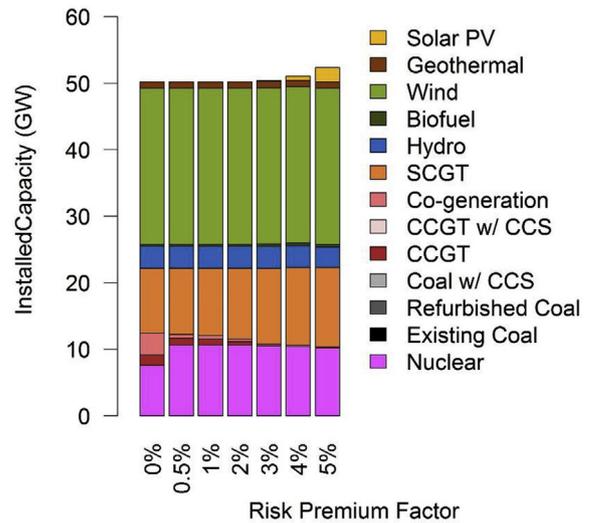


Fig. 10. Installed capacity by technology at various levels of risk premium in the year 2050 for system with nuclear available.

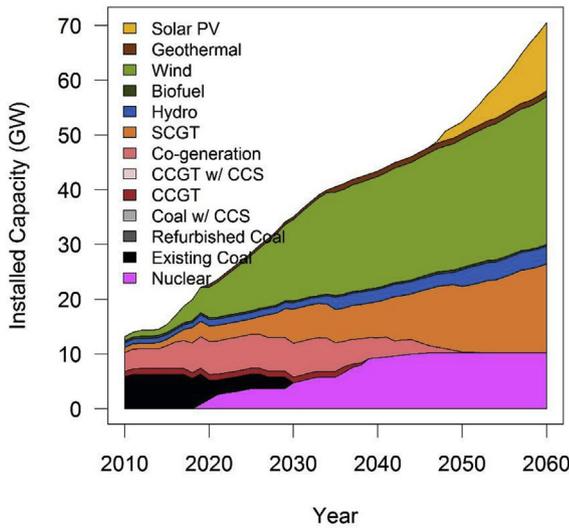


Fig. 9. Installed generation capacity over time for system with 5% risk premium and nuclear as a generation option.

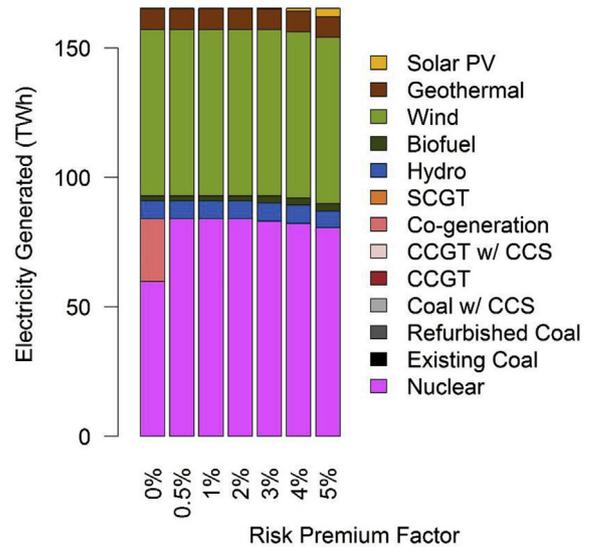


Fig. 11. Generation by technology at various levels of risk premium in the year 2050 for system with nuclear available.

enabled, SCGT technologies are installed to meet the reserve margin, but do not significantly contribute to the energy produced, as shown in Fig. 11. This figure shows that two types of generation, nuclear and wind, dominate across all risk premium levels. For the case with no consideration of the emissions risk, co-generation remains as a generation option meeting a portion of the heat demand for the oil sands. However, this is pushed out with only a 0.5% risk premium and is replaced by nuclear. Nuclear would likely also be able to supply this heat demand, so would be a reasonable replacement for co-generation. As the risk premium increases, small amounts of other technologies such as biomass and solar come in to the mix, but wind and nuclear comprise the majority of the generation in the system in all cases.

One consideration for this generation mix would be the interaction between nuclear and wind generation. Nuclear is not generally considered agile, so the coupling with variable wind generation might be technically challenging. Fig. 10 shows that there is a significant amount of SCGT installed to meet peaking

loads, but this generation is never used in the model due to the low resolution of the time slices, as seen in Fig. 11. In actual operation the SCGT might be called upon to meet the ramping requirements in the system. It is also possible that, with new nuclear technologies, that nuclear could meet the ramping requirements. Adaptations in existing plants and design features of new plants promise to allow nuclear to follow loads [66,67] and reactors in France have been used for load following for many years [68,69].

Fig. 12 shows the distributions of realized emissions for all 2000 random realizations of the generation emissions profiles. As was the case with the current no nuclear AESO projection, there is a clear trend of reduced average emissions with an increased risk premium. There is, however, notable difference between the trend with nuclear available and the trend with the current AESO projections without nuclear (Fig. 7).

For the case with no nuclear (Fig. 7), as the risk premium increases, average emissions and the high emission outliers follow the same decreasing trend and the maximum high emissions case

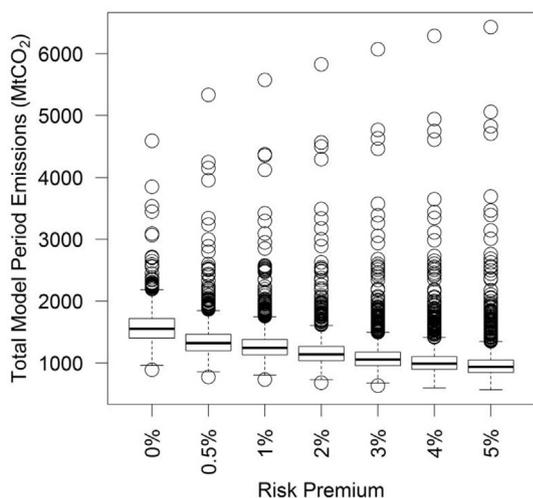


Fig. 12. Total model period emissions for each random realization at various levels of risk premium for system with nuclear available.

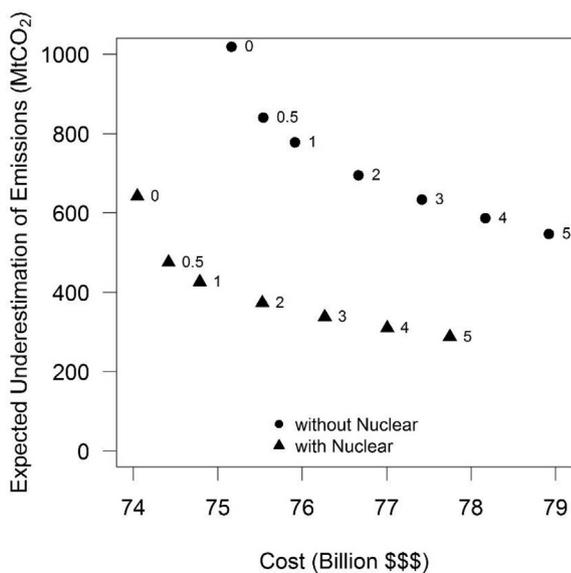


Fig. 13. Model calculated risk versus system cost for all risk premium levels for the system with and without nuclear.

is approximately 3500 MtCO₂. When nuclear generation is available (Fig. 12), the trend of average emissions show this same decreasing trend, with the average at each risk premium around 500 MtCO₂ lower than that without nuclear available. However, there are a number of high emissions outliers, which are as high as 4500–6000 MtCO₂. Both risk and average emissions are reduced, but there is a low probability (*i.e.* less than 10 in 2000 or less than 0.5%) that the emissions are higher. This is because the system relies on only two generation technologies. If either of the technologies produces emissions toward the upper end of its distribution, for a given random realization, the total emissions for that realization are high.

5.3. Cost and risk comparison

It is illustrative to compare the cost and risk for each risk premium for the systems with and without the option of nuclear

generation. Fig. 13 shows the Pareto optimal risk versus cost curves with and without nuclear available. This figure shows that the risk and cost are significantly lower for all situations where nuclear is available.

Fig. 13 shows that the risk with nuclear, at a 0.5% risk premium, is lower than the risk without nuclear at a 5% risk premium. Although there is much public controversy about nuclear safety, nuclear generation provides a cost effective hedge against climate emissions risk.

6. Discussion

We have used a stochastic risk framework and applied it to carbon emissions in an electrical system represented by the province of Alberta, Canada, a predominantly fossil based system, and have included nuclear as a risk mitigation technology.

We find that, for the system without the availability of nuclear in the generation mix, a 5% risk premium starts the build out of wind 5 years earlier, and the build out of solar photovoltaic 7 years earlier than the base model, ending up with significantly more installed solar in 2050 than without the risk premium. In the year 2040, coal with carbon capture and storage comes into the energy mix and replaces co-generation as a less risky alternative. Parkinson and Djilali [10] did not include carbon capture technologies in their model so the results cannot be compared directly, but their model also showed an increase in wind generation with increased risk premium and, similar to our results, they found an increase in SCGT to meet the reserve margin. Their model showed run of river and pumped hydro taking up the bulk of the generation while, in our model, CCS came in at higher risk premiums and pushed out CCGT. Since they analysed a primarily hydro based jurisdiction, using pumped storage and run of river technologies is possible. In the Alberta context, there is no significant potential for either run of river or pumped storage. This shows that jurisdictions with different potential energy sources need to be analysed separately. Our analysis could be extrapolated to similar fossil based jurisdictions such as many US states and countries such as India and China.

Although current climate policies eventually incent additions of renewables, additional policies that provide for earlier adoption of solar power and wind could provide a risk hedge against future emissions if nuclear is not considered an option. A policy to encourage earlier wind adoption would need to be implemented almost immediately, while the policy to encourage solar adoption would need to take effect in the early 2040s. Investments in the development of coal with CCS or other unproven low carbon technologies that can meet baseload with lower emissions risk could provide future benefits. Although this technology is not installed by the model until the early 2040s, similar to solar, the potentially lengthy research and development timelines would indicate that policy action sooner rather than later is needed. Using a risk framework to look at carbon dioxide emissions could allow decision makers to implement policies that are more effective given the timelines for some technologies.

With nuclear available for the system there is little power generated by any technology other than wind and nuclear, though some flexible generation in the system would be needed for system stability. This could be met by building nuclear generation able to ramp and follow load though we acknowledge that this could increase costs. If nuclear is considered an option for Alberta, the focus should be on getting the best performance out of the combination of wind and nuclear. Even without a risk premium applied, allowing nuclear reduces costs and reduces the risk of increased emissions and is installed starting around 2040. With a significant shift in social/political will, having nuclear generation operational in Alberta as early as 2020, and contributing significantly by 2030

reduces the emissions risk significantly if a 5% risk premium is applied. This is consistent with the results found by Kanudia et al. using a multi-scenario framework [47], who found that, when nuclear was available, it was always fully utilized in their model. We realize that a significant political and social shift would be required to allow nuclear to contribute to the Alberta power system in 2020 so early policy action would be needed to realize the full benefit of nuclear as a risk hedge if a 5% risk hedge is implemented as policy.

Our results show that nuclear is a cost effective risk hedge against increases in carbon dioxide emissions even without a risk premium applied. The 0% risk premium with nuclear case has the same emissions risk as the 3% risk premium without nuclear case, but at a 5% lower cost. As discussed in the literature review, there has been significant research into the cost uncertainty of nuclear but our results indicate that there is room for capital cost escalation in nuclear and it would still provide an effective risk hedge against increased emissions.

As noted in the literature review, very little work has been published on the risk of increased emissions in energy system modelling. More studies that investigate this space would provide more comparisons and allow for more detailed policy direction.

7. Future work

The model described above has a number of limitations that could be addressed in future work. The main limitation is that emissions from a number of technologies such as wind and solar occur only at the installation phase and not when the technology generates electricity. The current implementation of the model uses expected emissions per kWh generated, or leveled emissions, and therefore disadvantages these technologies. Separating out the risk associated with construction emissions will allow us to address this limitation.

The model implementation above uses Coal with CCS as a proxy for a low-emissions dispatchable/baseload generator. At this point CCS technology is still developing and there are unknown risks with the technology including the possibility of leakage from the stored carbon. Incorporating this risk into the model could alter the results and provide interesting insights.

In this study we investigated how to hedge against the risk of increased emissions while most studies on risk consider only financial risks. Developing a framework for incorporating both financial and emissions risks into the model would potentially provide insights into how to mitigate both financial and emissions risks and allow for more nuanced policy decisions.

Finally, expanding the study to include the entire energy system, not just the electricity system, would make the analysis more general. There may be some interesting trade-offs in terms of how to meet the given demand for these three services within this model framework.

Acknowledgements

The authors would like to acknowledge the financial support of the Pacific Institute of Climate Solutions (PICS) and the British Columbia Institute of Technology for their support of this work.

Appendix. : OSeMOSYS Code

To incorporate risk into OSeMOSYS the following sets, parameters, variables and constraints were added to OSeMOSYS.

Sets:

```
set RANDOMDRAWS;
```

Randomdraws is a sequential set from 1 to N, the number of random draws in the model run.

Variables:

```
var Risk >=<Roman> = </Roman>0;
var RiskNUp{n in RANDOMDRAWS} >= 0;
var RiskNDown{n in RANDOMDRAWS} >= 0;
```

Risk is the risk measure, which is comprised of only the upside risk as defined below. Two variables, RiskNUp and RiskNDown are used to allow the model to sum only the upside risk.

Parameters:

```
param BaseEmissionIntensity{t in TECHNOLOGY};
```

Baseline emissions intensity for each technology. This is the deterministic expected average emissions intensity for this technology with no consideration of uncertainty.

```
param EmissionsIntensity{n in RANDOMDRAWS,t in TECHNOLOGY};
```

The emissions intensity for each technology for each random draw. This is used to calculate the upside/downside risk.

```
param OptimalCost;
```

Cost of the 'optimal' system, without any risk hedging considerations.

```
param RiskPremiumFactor;
```

The risk premium factor for the model. How much more we are willing to pay to hedge against the risk.

Objective:

```
minimize risk: Risk;
```

We minimize the risk, which is calculated as the upside risk in constraint EQRiskSum.

Constraints:

```
s.t. EQRiskDraws{n in RANDOMDRAWS}: sum{y in YEAR, t
in TECHNOLOGY, l in TIMESLICE, r in REGION, m in MOD-
E_OF_OPERATION} (RateOfActivity [r,l,t,m,y] *
(BaseEmissionIntensity [t] - EmissionsIntensity
[n,t])) - RiskNUp [n] + RiskNDown [n] = 0;
```

For each random draw, this equation calculates the upside or downside risk for the given technology mix and operational decisions.

```
s.t. EQRiskSum: sum{n in RANDOMDRAWS} RiskNUp [n] =
(max{nn in RANDOMDRAWS} max (nn)) * Risk;
```

This equation sums the upside risk to calculate the overall risk in the system.

```
s.t. Cost: sum{r in REGION, t in TECHNOLOGY, y in
YEAR} (((((sum{yy in YEAR: y-yy < OperationalLife
[r,t] && y-yy >=<Roman> = </Roman>0} NewCapacity
[r,t,yy]) + ResidualCapacity [r,t,y])*FixedCost
[r,t,y] + sum{m in MODE_OF_OPERATION, l in TIME-
SLICE} RateOfActivity [r,l,t,m,y]*YearSplit [l,y]
*VariableCost [r,t,m,y]))/(1 + DiscountRate
```

$$\begin{aligned}
 & [r, t])^{(y - \min\{yy \text{ in YEAR}\} \min (yy) + 0.5)) + \text{Capital-} \\
 & \text{Cost} [r, t, y] * \text{NewCapacity} [r, t, y] / \\
 & ((1 + \text{DiscountRate} [r, t])^{(y - \min\{yy \text{ in YEAR}\} \min (yy))} + \text{DiscountedTechnologyEmissionsPenalty} \\
 & [r, t, y] - \text{DiscountedSalvageValue} [r, t, y]) + \text{sum}\{s \text{ in} \\
 & \text{STORAGE}\} (\text{CapitalCostStorage} [r, s, y] * \text{NewS-} \\
 & \text{torageCapacity} [r, s, y] / ((1 + \text{DiscountRateStorage} \\
 & [r, s])^{(y - \min\{yy \text{ in YEAR}\} \min (yy))}) - \text{Capital-} \\
 & \text{CostStorage} [r, s, y] * \text{NewStorageCapacity} [r, s, y] / \\
 & ((1 + \text{DiscountRateStorage} [r, s])^{(y - \min\{yy \text{ in YEAR}\} \\
 & \min (yy))})) \leq (1 + \text{RiskPremiumFactor}) * \\
 & \text{OptimalCost};
 \end{aligned}$$

We restrict the cost to being less than the optimal cost plus an additional risk premium factor.

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