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Hedging the risk of increased emissions in long term energy planning

T. Niet [a, b, *], B. Lyseng [a], J. English [a], V. Keller [a], K. Palmer-Wilson [a], I. Moazzen [a], B. Robertson [a], P. Wild [a], A. Rowe [a]

[a] Institute for Integrated Energy Systems, University of Victoria, PO Box 1700 STN CSC, Victoria, BC, V8W 2Y2, Canada
[b] School of Energy, British Columbia Institute of Technology, 3700 Willingdon Avenue, Burnaby, BC, V5G 3H2, Canada

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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.

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 CO_2 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]

* Corresponding author. School of Energy, British Columbia Institute of Technology, 3700 Willingdon Avenue, Burnaby, BC, V5G 3H2, Canada.
E-mail addresses: Taco_Niet@bcit.ca (T. Niet), bcl@uvic.ca (B. Lyseng), jre@uvic.ca (J. English), kellerv@uvic.ca (V. Keller), kevinpw@uvic.ca (K. Palmer-Wilson), imanmoaz@uvic.ca (I. Moazzen), bryson@uvic.ca (B. Robertson), pwild@uvic.ca (P. Wild), arowe@uvic.ca (A. Rowe).

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Nomenclature

$a_{i,j}$	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. Martienez-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