



Long-term energy planning with uncertain environmental performance metrics



Simon C. Parkinson^{a,b,*}, Ned Djilali^a

^a Institute for Integrated Energy Systems, University of Victoria, PO Box 3055 STN CSC, Victoria, BC V8W 3P6, Canada

^b International Institute for Applied Systems Analysis, Schlossplatz 1, A-2361 Laxenburg, Austria

HIGHLIGHTS

- Environmental performance uncertainty considered in a long-term energy planning model.
- Application to electricity generation planning in British Columbia.
- Interactions with climate change mitigation and adaptation strategy are assessed.
- Performance risk-hedging impacts the technology investment strategy.
- Sensitivity of results to model formulation is discussed.

ARTICLE INFO

Article history:

Received 22 August 2014

Received in revised form 10 January 2015

Accepted 1 February 2015

Keywords:

Energy technology

Environmental impact

Risk

Mathematical programming

ABSTRACT

Environmental performance (EP) uncertainties span a number of energy technology options, and pose planning risk when the energy system is subject to environmental constraints. This paper presents two approaches to integrating EP uncertainty into the long-term energy planning framework. The methodologies consider stochastic EP metrics across multiple energy technology options, and produce a development strategy that hedges against the risk of exceeding environmental targets. Both methods are compared within a case study of emission-constrained electricity generation planning in British Columbia, Canada. The analysis provides important insight into model formulation and the interactions with concurrent environmental policy uncertainties. EP risk is found to be particularly important in situations where environmental constraints become increasingly stringent. Model results indicate allocation of a modest risk premium in these situations can provide valuable hedging against EP risk.

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1. Introduction

Environmental resources are increasingly strained, with technological transitions in the energy sector sought to provide relief [1]. For long-term planners, policies that constrain the environmental impact of energy systems drive the need to rank technology options based on environmental performance (EP). Common EP metrics include the rate at which a technology emits greenhouse gases and other air pollutants [2], or consumes land and water resources [3,4].

Accurate EP quantification at the technology-level requires detailed knowledge of the end-use demands, location of implementation, and the supply chain that enables technology operation

[5,6]. The large-scale, spatially-distributed nature of modern energy systems means long-term planners often lack computational resources to perform analysis at the necessary resolution. Although lifecycle studies quantify EP uncertainty, long-term energy scenarios—developed to inform long-term planners—are typically generated with models operated under deterministic conditions. This approach poses risk when the planner must secure environmental targets: if technology is developed under the precondition it provides a certain level of EP, only to find out later it was overestimated, unforeseen changes to the energy strategy may be required. Potential measures include pre-mature retirement of capacity: a fate projected for much of the global coal-powered electricity generation under climate stabilization policy [7]. These *lock-in* effects are costly, and caused by the lengthy planning period and lifecycle associated with energy infrastructure, and the resulting inertia technology decisions impart into the entire energy supply chain [8]. To avoid similar

* Corresponding author at: Institute for Integrated Energy Systems, University of Victoria, PO Box 3055 STN CSC, Victoria, BC V8W 3P6, Canada.

E-mail address: scp@uvic.ca (S.C. Parkinson).

energy pathways, opportunities to mitigate EP risk should be considered within the long-term energy planning framework.

A number of previous studies tackle the issue of risk in long-term energy system planning. Uncertainties covered span a number of different components, including: technology costs and availability [9–14]; technological learning rates [15–17]; renewable resource availability and demand [18]; climate policy [19–21]; climate sensitivity [22–24]; or a combination thereof [25–35]. Relatively few studies examine implications of EP risk from the perspective of long-term energy planning. Technology efficiency scenarios were explored within a stochastic optimization framework [36,37]. Uncertain technology efficiency and emission factors were also addressed within a multi-criteria analysis [38]. The issue of natural gas lifecycle emissions uncertainty was further incorporated within a stochastic planning model [39]. This recent study demonstrates the importance of including uncertain EP into the long-term planning analysis, by quantifying the potential benefits of upstream emission controls on climate change mitigation costs.

The current study compares two approaches to integrating EP uncertainty into the environmentally-constrained long-term energy planning framework. The methodologies consider stochastic EP metrics across multiple technology options, and produce a development strategy that hedges against the risk of exceeding environmental targets. The models are applied to a case study of emission-constrained electricity generation planning in western Canada. The analysis provides important insight into model formulation and the interactions with concurrent environmental policy uncertainties.

2. Methodology

Mathematical programming is a frequently applied tool for resource planning analysis that enables representation of physical and institutional processes as a series of algebraic relationships and identification of solutions that optimize some overarching objective. Due to the large number of relationships requiring representation, linear models are typical in long-range energy planning studies [40–42]. Any linear programming problem can be represented in the following standard form:

$$\text{Min } \sum_j (c_j \cdot x_j) \quad (1a)$$

$$\text{s.t. } \sum_j (a_{ij} \cdot x_j) \leq b_i \quad \forall i \quad (1b)$$

$$x_j \geq 0 \quad \forall j \quad (1c)$$

The objective of the problem is to find the solution vector $\mathbf{x}$ (with elements x_j) that minimizes the function defined in (1a), subject to the constraints given in (1b) and (1c). For long-term energy planning, the solution vector represents the capacity and activity of energy technologies over the time horizon of interest. The objective is typically economic, and coefficients c_j therefore transform the solution vector into expenditures and revenue. The performance of individual technologies is represented by the technical input–output coefficients a_{ij} . These parameters determine the amount of constrained resource b_i consumed or provided by decision variable x_j . The subscript i therefore denotes a particular resource constraint with the subscript j denoting a particular decision variable.

Energy-related constraints include service requirements, fuel availability and capacity levels. Environmental constraints are also of increasing concern to energy planning, and are represented using the input–output coefficients to link development and operation of technologies to specific environmental impacts. An example is the inclusion of emission factors and emission constraints to

explore system configurations that ensure an emissions-level that remains below a desired target.

The linear programming model in its current form is deterministic, and therefore its utility in studying EP uncertainty is limited. Deterministic scenario analysis is an option; however, this strategy requires multiple model runs and a skilled analyst to identify robustness across the solution space [9]. Another method is to hedge against potential risks through explicit representation of uncertainties within the original problem framework.

One way of incorporating risk-hedging within the linear programming framework is to define a measure of risk R that inflates the original deterministic objective function [43]. The risk measure can be parameterized based on the total absolute deviation from the expected value, obtained based on successive draws from a known probability space [44]. Risk-hedging against EP uncertainties requires a different tactic, as these uncertainties concern the technical input–output coefficients. A similar approach translates the risk measure to the technical constraints [45,46]. Formulation of the linear programming problem with uncertain input–output coefficients can be represented by the following system of equations:

$$\text{Min } \sum_j (c_j \cdot x_j) \quad (2a)$$

$$\text{s.t. } \sum_j (\bar{a}_{ij} \cdot x_j) + \Phi_i \cdot R_i \leq b_i \quad \forall i \quad (2b)$$

$$\sum_j [(a_{ij,k} - \bar{a}_{ij}) \cdot x_j] - (r_{i,k}^+ - r_{i,k}^-) = 0 \quad \forall i, k \quad (2c)$$

$$\frac{1}{N} \cdot \sum_k r_{i,k}^+ - R_i = 0 \quad \forall i \quad (2d)$$

$$x_j, R_i, r_{i,k}^+, r_{i,k}^- \geq 0 \quad \forall i, j, k \quad (2e)$$

The mathematical programming model now considers stochastic technical coefficients $a_{ij,k}$, which are included as N realizations of the assumed uncertainty distributions. The subscript k denotes the particular realization of the stochastic coefficients included in the model. Constraint (2b) contains the risk term $\Phi \cdot R_i$, which is added to the technical performance obtained under the expected value of the input–output coefficients $\bar{a}_{ij}$. The risk term inflates resource usage above the expected value, and essentially provides a reserve margin. Following Messner et al. [9], the mean positive deviation from the expected value parameterizes the risk measure in (2d). The positive value is chosen to reflect that underestimating technical performance is more risky than overestimation.¹ Constraint (2c) computes the deviations obtained under each realization of the stochastic technical coefficients. The deviations are broken into positive and negative components $r_{i,k}^+$ and $r_{i,k}^-$ to preserve linearity. The parameter Φ is the risk aversion parameter, and its utility is sensitivity analysis of results, namely to varying decision-maker attitudes towards technical performance risk. The formulation allows for impact-specific risk aversion parameters to be specified, enabling preferential weighting of resource constraints.

A potential drawback of the above approach is the abstract nature of the risk aversion parameter and the expected difficulty in eliciting an appropriate value from non-technical decision-makers. These individuals are typically interested in understanding trade-offs between cost and risk reduction. An alternative approach based on available budgetary constraints is therefore proposed here, and is similar to that described in [34]. In this formulation, a risk premium quantifies the decision-maker's willingness to

¹ Arguably, both positive and negative risk should be penalized, as both impact the strategy costs at the expected (average) parameter values. This type of formulation can be achieved by defining a non-linear risk measure (e.g., linear-quadratic risk). Options are discussed in greater detail in [34]. The energy models explored in this paper implement linear solvers and thus this work is limited to linear programming solutions.

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