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Abstract

Economy-wide top-down equilibrium (TD) models have traditionally proved to be valuable tools for assessing energy and climate policies. New modeling challenges brought about by intermittent renewable energy sources, however, require to carefully review existing tools. This paper provides an overview of and quantitatively assesses the suitability of TD modeling approaches to deal with intermittent renewables in the electricity sector. To this end, we develop a benchmark model that integrates a bottom-up electricity sector model—designed to analyze the expansion and operation of an electric power system with a large penetration of wind generation—within an economy-wide general equilibrium framework. We find that, if properly specified, a TD approach to modeling intermittent renewable energy is capable of roughly replicating the results from the benchmark model. We argue, however, that for practical purposes TD modelers do not possess the required information. This problem is further compounded by our finding that a TD approach is highly sensitive to key parameters which are *a priori* typically unknown or at least highly uncertain. While the integrated approach presented in this paper offers one possible alternative to overcome some of the issues that plague traditional TD models, our analysis suggests that traditional TD simulation tools have to be enhanced to avoid potentially misrepresenting the implications of future low-carbon policies.

Keywords: Renewable Energy, Electricity, Intermittency, General Equilibrium, Top-down Modeling, Bottom-up Modeling

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1. Introduction

Traditional modeling approaches, both in the domains of economy-wide "top-down" (TD) equilibrium as well as engineering-type "bottom-up" (BU) models have proven to generate adequate and reliable model-based approximations of real-world energy (and electricity) production for systems characterized predominantly by fossil-based energy sources and technologies.[1] The substantial and rapid increase in energy production from renewable intermittent energy sources in many countries over the past two decades and their expected significant role in future energy systems represent, however, a major challenge for the further advancement of model-based simulation tools aimed at investigating integrated economy-energy systems. More specifically, sound modeling approaches should be able to capture the key characteristics of intermittent wind and solar energy resources with the necessary temporal and spatial detail as well as their energy system implications such as, for example, the need for "back-up" capacity and reserve sharing, system reliability, and incentives for investments in generation, storage, and transmission capacity. Macroeconomic TD simulation models are widely used analytical tools to investigate the impacts of energy and climate policy in terms of technological pathways, environmental impacts (i.e., greenhouse gas emissions reduction potentials) and their social costs (see, for example, TD models used in recent modeling community efforts such as the Energy Modeling Forum; Fawcett et al., 2014). While being prominently used for deriving policy recommendations—often with a large emphasis on renewable energy policies—the current generation of TD modeling approaches often seem to lack the required detail and relevant model features to convincingly represent intermittent renewable energy sources, or other technologies that could be of essence in the future, such as storage and demand response.

The objective of this paper is two-fold. First, we aim to provide a brief overview of existing TD approaches to represent intermittent energy sources, focusing on wind as a major renewable energy source. Second, we will investigate the suitability of TD approaches, as exemplified by the MIT EPPA (Paltsev et al., 2005b) and the MIT USREP general equilibrium models (Rausch et al., 2010) looking at the evolution of the energy mix with increasing penetration of wind under system reliability and resource adequacy constraints within an economy-wide modeling framework. To this end, we first develop a detailed recursive-dynamic BU model of the electricity sector which has been specifically designed to analyze the expansion and operation of an electric power system with a large penetration of wind (Tapia-Ahumada and Pérez-Arriaga, 2014). We put particular emphasis on a sufficient temporal resolution—i.e. an hourly characterization—of both wind resources and electricity demand to better capture the impact of intermittency on the system's expansion and

[1]TD models typically represent energy production technologies through highly aggregated (often smooth) production functions. While the strength of these models is to include energy supply and demand decisions within an internally consistent macro-economic framework, they typically lack the technological, spatial, and temporal resolution needed to adequately represent the energy system. BU models, on the other hand, typically feature a highly resolved and technology-rich representation of energy (supply and demand) technologies but fail to include interactions with the broader economic system due to their partial equilibrium nature. Importantly, BU models are hence not capable of incorporating macro-economic determinants of energy demand and supply and they cannot assess policies in terms of their social cost (e.g., GDP or consumption impacts). See, for example, Hourcade et al. (2006) for a more in-depth overview and discussion of both modeling paradigms.

operation in the long-term.[2] In a second step, we then fully integrate this BU model within a TD general equilibrium framework to obtain a benchmark model against which we can evaluate the performance of a stand-alone TD approach to modeling intermittent renewable energy. The TD component of our integrated model is based on the MIT U.S. Regional Energy Policy (US-REP) model, a recursive-dynamic, multi-sector multi-region numerical general equilibrium model designed to analyze climate and energy policy in the U.S. (Rausch et al., 2010, 2011).

On a more general level, the goal of the analysis is therefore to examine the implications of different structural modeling choices within general equilibrium models with respect to representing intermittent renewable energy sources. Given the wide-spread use and increasing importance of numerical general equilibrium models to assess the impact of and derive recommendations for energy and climate policies, we believe that it is important to shed light on the conceptual foundations that underlie the representation of intermittent renewables in electricity generation. While it should be clear that one cannot derive general qualitative insights from such a model-based assessment, and that in particular the results presented here are based on comparing a BU approach with one particular TD approach, we nevertheless believe that the present analysis will help contribute to understanding the usefulness and limitations of employing numerical simulations models for the economic (policy) analysis of integrated economy-energy systems with significant levels of energy production from highly intermittent renewable energy sources.

Our analysis is germane to the literature on integrating TD and BU models for carbon policy assessment (see, for example, Hourcade et al., 2006, for an overview). Following the seminal methodological contribution of Boehringer and Rutherford (2009) on "hardlinking" TD and BU models, an important feature of our modeling approach is that electric-sector optimization, including modeling detail to represent intermittent generation from wind energy, is fully consistent with the equilibrium response of the economy including endogenously determined electricity demand, fuel prices, and goods and factor prices. There are only a few studies which have fully integrated a TD general equilibrium model with a BU electricity-sector model in an applied large scale setting. Sugandha et al. (2009) employ a hybrid TD BU modeling approach, but their modeling framework has considerably less detail with respect to modeling important features of renewable electricity generation. Rausch and Mowers (2013) link a economy-wide general equilibrium model to NREL's ReEDS (Renewable Energy Deployment System) model (Short et al., 2011), a recursive-dynamic linear programming model that simulates the least-cost expansion of electricity generation capacity and transmission, with detailed treatment of renewable electric options., 2013). They do not, however, investigate the question of the suitability and performance of alternative modeling approaches to intermittent renewable energy.

Our results are as follows. First, the use of an integrated model with a more refined characterization of the electricity sector enables capturing more realistically the long-term adaptation of a system to the penetration of wind. It is observed that wind grows up only to the level where revenues are still attractive enough to recover overall costs, and that increased wind penetration reduces the electricity prices precisely when wind production is higher, preventing this technology

[2] It is becoming widely accepted that the presence of large volumes of intermittent renewable generation (wind and solar PV, typically) profoundly modifies the operation and the optimal generation mix of power systems, in ways that cannot be predicted in the absence of suitable detailed models (Pérez-Arriaga and Batlle, 2012).

from having an even larger penetration. This feature is missed in coarser representations of wind technology as represented in conventional TD general equilibrium approaches. Second, the paper provides evidence with regard to the importance of key assumptions, implicitly and explicitly made in TD approaches. Results show that a sophisticated calibration is needed to obtain results that would be consistent with the integrated model for large penetration levels of wind. We find that our TD approach is highly sensitive with respect to the assumed values for key parameters such as the relative costs of the technologies, elasticities of substitution between wind resource and non-resource factors, and the initially specified amount of wind resources as well as their rate of penetration. Assuming *a priori* reasonable ranges for critical input parameters in the TD model, we find that key model outputs such as the level of wind penetration and CO_2 emissions can vary substantially: wind penetration ranges from 0% to 43% (of total electricity generation) and CO_2 emissions range between -6% and +60% for future model periods with respect to a central case parametrization. Based on the inherent difficulty to adequately parameterize the TD model, we thus argue that an integrated modeling approach, which exhibits sufficient resolution of the electric sector and in particular with respect to features relevant for intermittent renewable technologies, is needed to provide a robust characterization of the future energy system and to assess energy and climate policies.

The paper is organized as follows. Section 2 provides a brief overview of modeling approaches to represent intermittent renewables in TD general equilibrium models, taking the MIT USREP model as an example. Section 3 provides an description of the BU model for the electricity sector and details the methodology adopted to integrate the TD and BU modeling approaches. Section 4 investigates the suitability of the integrated modeling approach to represent renewables and compares its performance to a TD-only approach. Section 5 concludes.

2. Intermittent renewable energy in TD general equilibrium approaches

2.1. Overview of alternative TD approaches

It is acknowledged in the literature (see, for example, 2009, Labandeira et al.)—and seems to be common knowledge in the TD modeling community—that the electricity sector is difficult to represent using TD models, in particular when disruptive renewable energy technologies are concerned. Recognizing the need to incorporate new low-carbon technologies, different techniques have been used in TD Computable General Equilibrium (CGE) models to portray technological change in the power sector, in particular with respect to low-carbon technologies. There are, however, several issues that arise from the conceptual nature of TD CGE models that constitute challenges or even limitations for appropriately representing energy production from intermittent renewable energy sources.

First, TD approaches typically do not explicitly model the electricity dispatch but rather use historical data to benchmark the initial conditions of the economy and stylized production functions to assess changes in generation driven by price variations in fuels and other production inputs.

Second, TD CGE models rely on Constant Elasticity of Substitution (CES) production functions to depict production activities. Key modeling assumptions within a CGE context related to electricity generation then entail specifying whether or not electricity is a homogeneous good (i.e., electricity supplies generated from different technologies are perfect or imperfect substitutes) and picking a nested substitution structure between conventional fossil fuel-based generation, nuclear, hydro and new advanced technologies. Also, modelers specify the substitution structure between inputs to production within each of the different technologies. The unique attributes of the non-extant low-carbon technologies need to be captured through the parameters of the CES function.

Third, as substitution and complementarity patterns of non-dispatchable technologies are not known *a priori*, multiple ad-hoc assumptions are needed in TD models to approximate the costs of maintaining system reliability in power systems, for example through the the representation of backup generation and other sources of operational flexibility such as transmission networks, storage devices, short-term demand response and hydro power. More often than not, these other sources of flexibility are fully ignored or are highly aggregated in some of the parameters used to represent the production processes.

The literature documents efforts to improve the representation of renewables in economy-wide TD models. The aim here is not to exhaustively survey the literature but rather to provide a rough taxonomy of approaches that have been adopted so far. Subsequent sections will then describe in detail one particular approach that is implemented in our numerical framework for further exploration. First, TD models like the IGEM models—an econometrically estimated GE model of the U.S. economy (Goettle et al., 2009) which is used by the U.S. Environmental Protection Agency (EPA)—do not provide any breakdown of electricity technologies.[3] Second, TD general equilibrium models like ADAGE (Ross, 2009) and older versions of the EPPA model (Paltsev et al., 2005a) explicitly represent three broad electricity technologies: fossil fuel, non-fossil fuel and new advanced technologies. The modeling of wind and solar technologies follows the approach outlined in Paltsev et al. (2005a) where intermittent renewables are considered to be imperfect substitutes vis-à-vis fossil-based electricity generation. The penetration pattern of intermittent renewable technologies is controlled by means of the *ex-ante* specification of a low-substitution elasticity and a renewable resource factor that is assumed to be in fixed supply, thereby implicitly calibrating a resource cost supply curve for each renewable energy type. A problematic shortcoming under this approach is to abstract from the necessary temporal and spatial resolution. Third, the WITCH model (Bosetti and Tavoni, 2009) uses utilization factors to represent renewables, which can increase up to a pre-determined bound within a given time frame. Penetration patterns are furthermore influenced by ad-hoc choices about learning costs and reduced investment costs. Importantly, the WITCH model does not explicitly add restrictions to reflect the cost of intermittency into the power mix. Four, the GTEM model uses a "technology bundle" specification that includes 14 electricity technologies (including renewables), each of them with a different mix of inputs in fixed proportions according to its output (Pant, 2007). The main idea of this specification is to approximate a BU solution by restricting the solution space using the so-called CRESH (constant ratio elasticity of substitution homothetic production function; Hanoch, 1971) aggregate production function, which allows a smooth substitution between technologies and avoids a "winner-takes-all" behavior. It is assumed, however, that the technologies differ only with respect to their specific input costs, thereby not taking into account any of the time dynamics that are par-

[3] U.S. EPA uses the Integrated Planning Model (IPM), a multi-regional model of the U.S. electric power sector to analyze electricity sector impacts but the BU model component is not linked to a TD model, and hence does not interact—in a *fully* consistent way—with any of the economy-wide models used by EPA.

ticularly relevant for intermittent renewables. Moreover, electricity is a homogenous good from the consumer perspective but not from the supply side, which causes inconsistencies in the GE setting and potentially problems with welfare accounting. Fifth, another category of TD models (Paltsev et al., 2005a; Rausch et al., 2011) is based on an approach put forward by (Morris et al., 2010) which treats electricity as a homogeneous good and specifies "synthetic" electric generation technologies that combines intermittent renewable energy with backup technologies in order to render intermittent renewable energy technologies fully dispatchable (and thus to make them comparable with dispatchable fossil-based technologies).

We will next describe in detail the latter approach to represent intermittent renewable energy in TD general equilibrium modeling.

2.2. TD modeling of electricity generation from intermittent wind resources in the EPPA/USREP models

Electricity generation is portrayed by the cost minimization problem[4] of homogeneous firms in the electricity sector following a nested CES cost function (production technology), allowing price-driven substitution of inputs and taking into account resource availability and institutional constraints that control the penetration of new generation technologies. The penetration control constraints of renewable energy are captured by introducing an additional quasi-fixed factor input that represents the adjustment costs typically observed when new technologies are introduced in the system[5] (Paltsev et al., 2005a; McFarland et al., 2004). This factor can be thought as the costs of accumulating engineering knowledge and regulatory capacity to scale up new technologies. Following Paltsev et al. (2005a) and Morris et al. (2010), the EPPA/USREP represents three different wind technologies identified as *wind*, *windgas* and *windbio*. At low penetration levels, renewables are assumed imperfect substitutes and its electricity share is exogenously controlled. At higher penetration levels, wind requires back-up capacity to enter the generation mix and is modeled by using two artificial technologies: large-scale wind with 100% natural gas backup (*windgas*) and large-scale wind 100% biomass backup (*windbio*). Both technologies constitute perfect substitutes for electricity from dispatchable sources (Rausch et al., 2010; Rausch and Karplus, 2013).

The penetration pattern of wind in the TD approach largely depends on four key modeling choices:

1. *Nested CES structure* defines how the different technologies compete in the generation mix, and how inputs to production are combined to produce electricity in each of the technologies (see Figure 1 for one possible choice, which is adopted in the EPPA and USREP models).

[4]General equilibrium is cast as a mixed complementarity problem (MCP) based on the microeconomic principles underlining the Arrow-Debreu general equilibrium theory (Mathiesen, 1985). The MCP solves a system of non-linear equations to find the optimal value of prices, production and consumption levels, and consumers income. The complementarity condition implies that while prices and levels are associated with an equilibrium condition, the condition might be slack or non-binding if the associated variable is zero. Cost minimizing and price-taking behavior implies that zero-profit and market clearing conditions have complementary slackness with respect to production levels and market prices, respectively (Markusen and Rutherford, 2004).

[5]The fixed factor is also used to introduce other advanced technologies in EPPA/USREP, such as advanced nuclear and coal and natural gas with carbon capture and sequestration following Paltsev et al. (2005a).

2. *Elasticities of substitution* govern the substitution between electricity generation from wind and non-wind resources and are used to represent wind resource supply curves by formulating a trade-off between a capital-labor composite and a (inelastically supplied) wind resource factor.
3. *"Mark-up" factors* describe the cost of the first MWh of wind generated relative to the cost of a conventional benchmark technology (e.g., pulverized coal).
4. *Supply of the renewable resource factor over time* describes the availability of wind resources at a given point in time and is used to control the penetration pattern of wind technologies over time.

The remainder of this section describes (i) the modeling rationale behind each of these four features to represent intermittent wind energy and (ii) discusses the potential conceptual shortcomings on this approach.[6]

2.2.1. Nesting structure and equilibrium equations

This section lays out the equilibrium equations and describes the main parameters that govern the penetration pattern of wind technologies, using *windgas* technology as an example. A summary of the variables, parameters and benchmark value shares is presented in Tables A.1, A.2, and A.3 of Appendix A.

The nesting structure for total electricity generation is depicted in Figure 1. At the top-level, small-scale wind —which is modeled as an imperfect substitute— trades off with other technologies. At the second level, all technologies (fossil, nuclear, hydro and wind technologies) are perfect substitutes implying that electricity is a homogeneous good. We now focus on the *windgas* technology to explain the TD approach implemented here to represent intermittent wind.

The zero-profit condition, which determines the generation of electricity from *windgas* in each period, is given by:[7]

$$-\pi^{\text{windgas}} \geq 0 \perp \text{ELE}^{\text{windgas}} \geq 0 \tag{1}$$

where π^{windgas} denotes the unit profit function of the *windgas* technology.[8] Assuming a nested CES structure for *windgas*, as shown in Figure 1, π^{windgas} can be derived from the dual cost minimization problem:

$$\pi^{\text{windgas}} = \text{P}^{\text{ELE}} - \left(\left(\theta^{\text{FF}} \left(\mu_{\text{windgas}} \frac{P^{\text{FF}}}{\overline{P}^{\text{FF}}} \right)^{1-\sigma_{\text{FF}}} + \theta^{\text{KLG}} \left(\mu_{\text{windgas}} \frac{P^{\text{KLG}}}{\overline{P}^{\text{KLG}}} \right)^{1-\sigma_{\text{FF}}} \right)^{\frac{1}{1-\sigma_{\text{FF}}}} \right) \tag{2}$$

Wind is required to operate with 100% backup capacity provided here by a gas turbine. The perfect complementarity between both technologies is reflected by a Leontief structure, i.e. $\sigma_{VAG} =$

[6] We focus here on renewable energy technologies only, i.e. we do not revisit the standard approach to modeling dispatchable technologies. The structure and equilibrium conditions for conventional fossil generation, hydro and nuclear technologies in EPPA and USREP are described in Lanz and Rausch (2011).

[7] For ease of exposition we suppress here the region and time indexes.

[8] The "⊥" operator indicates the complementary relationship between the equilibrium condition and the associated variable; here, the zero-profit condition and the production level of wind electricity, ELE^{windgas}.

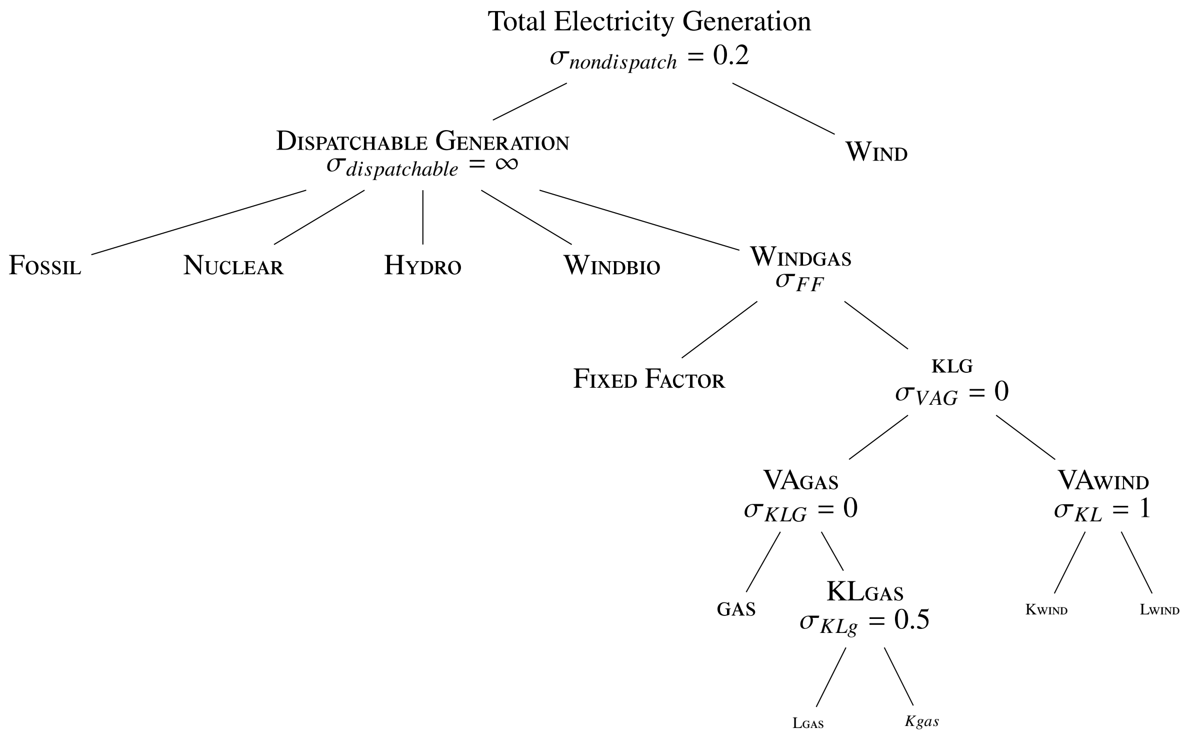

Figure 1: Nesting structure for electricity generation. *Note:* The figure depicts only *windgas* technology in the lower levels. For fossil, nuclear and hydro see Lanz and Rausch (2011).

0. The price of the capital-labor-gas composite, P^{KLG}, is given by:

$$P^{KLG} = \theta^{VAwind}\left(\frac{P^{VAwind}}{\overline{P}^{VAwind}}\right) + \theta^{VAgas}\left(\frac{P^{VAgas}}{\overline{P}^{VAgas}}\right) \tag{3}$$

where,

$$P^{VAwind} = \left(\theta^{K}_{wind}\left(\frac{P^{K}}{\overline{P}^{K}}\right)^{1-\sigma_{KL}} + \theta^{L}_{wind}\left(\frac{P^{L}}{\overline{P}^{L}}\right)^{1-\sigma_{KL}}\right)^{\frac{1}{1-\sigma_{KL}}}$$

$$P^{VAgas} = \theta^{KL}_{gas}\left(\frac{P^{KL}}{\overline{P}^{KL}}\right) + \theta^{gas}\left(\frac{P^{gas}}{\overline{P}^{gas}}\right)$$

$$P^{KL} = \left(\theta^{K}_{gas}\left(\frac{P^{K}}{\overline{P}^{K}}\right)^{1-\sigma_{KLg}} + \theta^{L}_{gas}\left(\frac{P^{L}}{\overline{P}^{L}}\right)^{1-\sigma_{KLg}}\right)^{\frac{1}{1-\sigma_{KLg}}}$$

The equilibrium conditions for electricity generation from the other wind technologies (i.e., ELE^{windgas}, ELE^{windbio}, and $ELE^{\text{windnobackup}}$) can be derived similarly, following the nesting structure for *windbio* and *wind* as shown in Figures A.9-A.10 of Appendix A. Using the production levels for electricity generation from ELE^{Fossil}, ELE^{Nuclear}, ELE^{Hydro} and the three wind technologies (summarized by ELE^{wind}) the market clearing condition for electricity is then given by:

$$ELE^{\text{Fossil}} + ELE^{\text{Nuclear}} + ELE^{\text{Hydro}} + ELE^{\text{wind}} = Demand^{\text{Ele}} \quad \perp \quad P^{\text{Ele}} \tag{4}$$

Equilibrium interactions of the electricity sector with the rest of the economy are described by a set of market clearing conditions for capital, labor, and resource markets. Equations (5)-(6) give the capital and labor market equilibrium conditions respectively.

$$K = D^{\mathrm{K}} + \overline{ELE}^{\mathrm{fossil}} \frac{\partial \pi^{\mathrm{fossil}}}{\partial P^{\mathrm{K}}} + \overline{ELE}^{\mathrm{hydro}} \frac{\partial \pi^{\mathrm{hydro}}}{\partial P^{\mathrm{K}}} + \overline{ELE}^{\mathrm{nuclear}} \frac{\partial \pi^{\mathrm{nuclear}}}{\partial P^{\mathrm{K}}} + \overline{ELE}^{\mathrm{wind}} \frac{\partial \pi^{\mathrm{wind}}}{\partial P^{\mathrm{K}}} \perp P^{\mathrm{K}} \quad (5)$$

where K is the capital supply, D^{K} is the capital demand from non-electricity sectors, $\overline{\mathrm{ELE}}$ denotes the benchmark value of electricity production from the different technologies, and $\frac{\partial \pi^{\mathrm{fossil}}}{\partial P^{\mathrm{K}}}$, $\frac{\partial \pi^{\mathrm{hydro}}}{\partial P^{\mathrm{K}}}$, $\frac{\partial \pi^{\mathrm{nuclear}}}{\partial P^{\mathrm{K}}}$, $\frac{\partial \pi^{\mathrm{wind}}}{\partial P^{\mathrm{K}}}$ denote the change in the unit cost function given a change in the price of capital P^{K} for each of the electricity technologies.

$$L = D^{\mathrm{L}} + \overline{ELE}^{\mathrm{fossil}} \frac{\partial \pi^{\mathrm{fossil}}}{\partial P^{\mathrm{L}}} + \overline{ELE}^{\mathrm{hydro}} \frac{\partial \pi^{\mathrm{hydro}}}{\partial P^{\mathrm{L}}} + \overline{ELE}^{\mathrm{nuclear}} \frac{\partial \pi^{\mathrm{nuclear}}}{\partial P^{\mathrm{L}}} + \overline{ELE}^{\mathrm{wind}} \frac{\partial \pi^{\mathrm{wind}}}{\partial P^{\mathrm{L}}} \perp P^{\mathrm{L}} \quad (6)$$

where L is the labor supply in the economy, D^{L} is the demand for labor from non-electricity sectors, and $\frac{\partial \pi^{\mathrm{fossil}}}{\partial P^{\mathrm{L}}}$, $\frac{\partial \pi^{\mathrm{hydro}}}{\partial P^{\mathrm{L}}}$, $\frac{\partial \pi^{\mathrm{nuclear}}}{\partial P^{\mathrm{L}}}$, $\frac{\partial \pi^{\mathrm{wind}}}{\partial P^{\mathrm{L}}}$ denote the change in the unit cost function given a change in the price of labor P^{L} for each of the electricity technologies.

In the case of wind technologies, the fixed factor has a fictitious market that clears according to condition (7), while the clearance condition of the gas market[9] is given by (8).

$$S^{\mathrm{wind}} = \overline{ELE}^{\mathrm{wind}} \frac{\partial \pi^{\mathrm{wind}}}{\partial P^{\mathrm{wind}}} \quad \perp \quad P^{\mathrm{FF}} \quad (7)$$

$$S^{\mathrm{gas}} = D^{\mathrm{gas}} + \overline{ELE}^{\mathrm{fossil}} \frac{\partial \pi^{\mathrm{fossil}}}{\partial P^{\mathrm{gas}}} + \overline{ELE}^{\mathrm{windgas}} \frac{\partial \pi^{\mathrm{windgas}}}{\partial P^{\mathrm{gas}}} \quad \perp \quad P^{\mathrm{gas}} \quad (8)$$

where S^{wind} is the supply of the fixed factor resource for wind, $\overline{ELE}^{\mathrm{wind}}$ is the benchmark production of wind, and $\frac{\partial \pi^{\mathrm{wind}}}{\partial P^{\mathrm{wind}}}$ denotes the change in wind unit cost given a change in the price of wind resource fixed factor P^{FF}.

2.2.2. *Elasticities of substitution*

At low penetration levels, wind technology is modelled as an imperfect substitute of dispatchable generation. The values adopted for elasticity of substitution $\sigma_{\mathrm{nondispatch}}$ result in a relatively inelastic supply, reaching at most 15% to 20% of electricity supply in any region. In order to represent a larger penetration, *windgas* and *windbio* technologies enter as perfect substitutes, i.e. $\sigma_{\mathrm{dispatchable}} = \infty$ (see Figure 1 above).

One key decision to control the penetration pattern of *windgas* and *windbio* technologies are the region-specific elasticities of substitution for the fixed resource factor, σ_{FF}, as shown in equation (2). σ_{FF} is derived by fitting wind supply-cost curves. The use of supply-cost functions for geographically distributed renewable energy is a useful tool to assess the physical and technical

[9] The description of the markets of other fossil fuels is not included here, since they do not enter the production process of *windgas* technology.

potential of these resources widely used in energy planning (see, for example, (Izquierdo et al., 2010)). For the USREP model, wind supply curves are constructed by estimating the cost per MWh using wind resource data from NREL[10], and cost assumptions to calculate the levelized cost of electricity (LCOE) of different wind classes in each U.S. region. These supply curves result in high quality wind resources having lower LCOEs than the low quality ones, with good wind sites being used first and new wind capacity becoming more expensive. Normalizing price to one, σ_{FF} is estimated from wind supply curves according to:

$$\frac{\partial \log Q}{\partial \log LCOE} = \sigma_{FF} \frac{\left(1 - \theta^{FF}\right)}{\theta^{FF}} \tag{9}$$

where Q is the electricity output, $LCOE$ is the levelized cost of electricity of harnessing that power, σ_{FF} is the price elasticity of supply, and θ^{FF} is the benchmark value share of the fixed factor. The details of these calculations are presented in Rausch and Karplus (2013), which entail the fitting of regional wind supply curves using ordinary least square procedure. See also Table A.4 of Appendix A for the datasets used in the case of the USREP model.

2.2.3. Mark-up technology parameters

Wind technologies enter the generation mix according to their relative cost competitiveness vis-à-vis conventional generation technologies as measured by a mark-up parameter μ_{n}, which represents the cost of the first MWh of wind generated with technology n relative to the benchmark cost of electricity generated with pulverized coal. As shown in equation (2) above, the mark-up of the *windgas* technology is a multiplier of both the price of fixed factor P^{FF} and the price P^{KLG} of the composite capital-labor-gas. If μ_{n} were greater than the benchmark price for electricity, wind technologies would not be competitive vis-à-vis conventional generation and, consequently, would not enter the energy mix.

The $LCOE$ of the minimum cost site for each wind technology is used in order to compute the parameter μ_{n}. These calculations need key assumptions to estimate the costs of the combined *windgas* and *windbio* technologies, such as the level of back-up capacity required for each MW installed of wind capacity and their corresponding utilization factors. Following the approach proposed by Morris et al. (2010), it is assumed that each MW of *windgas* technology requires 1 MW of a natural gas combined cycle (NGCC) to offset intermittency, with the wind turbine operating 35% of the time and the NGCC operating 7% of the time. The $LCOE$ of the combined *windgas* technology therefore has a higher input requirement of capital, labor and other costs to provide the additional back-up capacity and natural gas fuel requirements (similar assumptions are adopted for *windbio*, but considering the costs of a biomass plant). Based on the calculated LCOEs for the different technologies, the mark-up parameter μ_{n} is estimated according to:

$$\mu_n = \frac{LCOE_n}{LCOE_{coal}} \tag{10}$$

[10]Wind supply curves are constructed using U.S. wind resource availability estimates according NREL's Wind Integration Studies datasets. Source: *//www.nrel.gov/electricity/transmission/data_resources.html.*

where $LCOE_{\mathrm{n}}$ and $LCOE_{\mathrm{coal}}$ denote the LCOE for wind technology and pulverized coal, respectively.

The calculated mark-up varies per technology and region. For the New England region, for instance, the mark-up for *wind* ($\mu_{\mathrm{wind}} = 1.3$) indicates that the LCOE of wind is 30% higher than the LCOE of coal at the benchmark year. Accordingly, the mark-up for *windgas* ($\mu_{\mathrm{windgas}} = 1.6$) indicates that this technology is 60% more expensive than coal. Refer to Table A.5 of Appendix A for calculated regional mark-up values.

2.2.4. Resource supply and dynamics over time

The fixed factor controls the technology penetration pattern, once it becomes competitive. As shown in equation (2) above, the production of a unit of *windgas* electricity is a function of the price of the fixed factor P^{FF}. If the price of the fixed factor is too high, we can substitute this factor for other inputs to production at a price P^{KLG} with an elasticity of σ_{FF}. However, if the price of the fixed factor is too high and the possibility to substitute away from it is too small, the production of *windgas* is limited or non-existent. By the condition stated in equation (1), if unit profit is zero or negative then the complementary production variable ELE^{windgas} is zero. The price of the fixed factor P^{FF} is determined in a fictitious market defined for this factor and with a clearing condition as shown in equation (7).

In any given period, the resource S^{wind} is fixed and specified with a very small amount $inish^{\mathrm{wind}}$ in the first period. If supply is fixed, an increase in demand results in a higher market price but does not change the quantity. Therefore, renewable generation is very limited if the supply of the fictitious fixed factor S^{wind} in the economy is too small. The resource is allowed to grow as a function of previously installed capacity of wind technologies, reflecting the idea of initial adjustment costs and benefits of learning as technologies are deployed and mature. The dynamics for resource supply factors are formalized by the following equations:

$$S^{wind}_{t=2} = S^{wind}_{t=1} + inish^{wind}\,\theta^{FF}\,\mu_{windgas}\,ELE^{windgas}_{t} \tag{11}$$

$$S^{wind}_{t>2} = S^{wind}_{t=2} + \theta^{FF}\,\mu_{windgas}\,\overline{P}^{ELE}\alpha\,ELE^{windgas}_{t} + \beta\,ELE^{windgas\varsigma}_{t} \tag{12}$$

where $S^{\mathrm{wind}}_{\mathrm{t}}$ is the wind fixed factor supply in period t; $inish_{\mathrm{wind}}$ is the parameter that initializes the fixed endowment; θ^{FF} is the benchmark value share of the fixed factor; μ_{windgas} is the mark-up parameter; $\overline{\mathrm{P}}^{\mathrm{ELE}}$ is the benchmark price for electricity; $ELE^{\mathrm{windgas}}_{\mathrm{t}}$ is the production level of windgas technology in period t; and α, β and ς are parameters that allow a smooth penetration of the technology[11].

2.2.5. Shortcomings of the TD approach to modeling intermittent renewable energy

In summary, the TD approach outlined above provides a structure to incorporate detailed estimates of wind resource potentials through calibrating resource supply curves, and readily incorporates assumptions about technology costs, such as capital and fuel requirements. Moreover,

[11] They are calibrated so that the penetration follows an S shape form, as is typically observed in reality for the penetration patterns of new technologies.

parameters to control the penetration pattern of technologies are based on the observation that their market share grows gradually, even when the technologies are competitive. Notwithstanding these model features, we do believe that several shortcomings still exist.

First, an implicit assumption in the mark-up estimation—using a reference cost for LCOE—is that electricity coming from the different technologies can be used as base-load generation and compared as such. As Joskow (2011) and others have discussed, this statement is untenable in the case of renewable electricity generation whose value is highly dependent on the season and time of day at which the resource is available. Therefore the use of LCOE is incorrect to compare these technologies with dispatchable generation.

A *second* shortcoming lies in the formulation of wind without and with backup technologies. The approach without backup determines ex-ante the maximum penetration level and it can be highly sensitive to the elasticity of substitution. The selection of this value is (in principle) arbitrary given that wind could scale up beyond that level, depending on the specific characteristics of the electricity system. In the TD approach with back-up capacity, several assumptions are inaccurate in terms of truthfully portraying the power system operation. For example, it is unrealistic to assume that wind requires 100% backup capacity that is only used for backup purposes. It is well documented that wind capacity credit decreases gradually as a function of wind penetration (see for example NERC (2009) and Holttinen et al. (2011)), and that a mix of different technologies within the energy portfolio provides the required reserves (not only CCGT or bioelectricity, as assumed in the TD approach). Also, the assumption of having a low capacity factor (7% for NGCCs) does not guarantee the recovery of costs for backup technologies. More generally, wind or solar are not the only technologies that demand backup; for example, inflexible nuclear plants also need flexible generation to follow demand or to provide fast operating reserves in the case a large nuclear plant shuts down. Another factor to consider is that the average variable operating costs of the thermal generation units grow significantly with the penetration of intermittent generation.

Third, while introducing resource constraints in the TD model is desirable, the use of LCOEs to build the supply curve might overestimate the resource (underestimate the resource costs) since the costs of maintaining reliability (are likely to) increase as a function of wind penetration.

A *final* shortcoming is that the results of the TD model can be sensitive to the specification of certain parameters. In particular, the estimation of the mark-up μ_n parameter impacts the penetration of renewables since it determines the competitiveness of the technology. Since it is based on LCOE and different static assumptions regarding backup requirements, it is difficult to capture in this parameter the real market value of renewables. In addition, the penetration pattern is sensitive to the parameterization of the fixed factor S_t^{wind}, where the elasticity of substitution between the fixed factor and other inputs σ_{FF}, the benchmark value share of the fixed factor θ^{FF}, and the total initial endowment of the fixed factor *inish*, all play a critical role in determining whether or not the fixed factor constraint is binding.[12]

Given the shortcomings we have identified above on a conceptual level, a natural next step is to investigate their ramifications in a large-scale quantitative modeling framework.

[12] The input share θ_n^{FF} is also a critical parameter. However, to maintain consistency between the Social Accounting Matrix (SAM) and the engineering BU data (where this parameter does not exist), this share is relatively small. Therefore, results are not very sensitive to this parameter.

3. An integrated model approach to represent intermittent wind energy

We propose an integrated approach to model intermittent wind energy within an economy-wide GE framework that encompasses two sub-models coupled via an iterative algorithm, similar to the framework implemented by Rausch and Mowers (2013) and in line with the decomposition method presented by Boehringer and Rutherford (2009). The first component is the MIT USREP general equilibrium model, a multi-region multi-commodity economy-energy general equilibrium model of the U.S. economy (Rausch et al., 2010, 2011). The second one is a detailed BU capacity expansion and economic dispatch model of the electric power sector designed to investigate the system's operation with large penetration levels of wind.

The electricity model (hereinafter referred to as EleMod) has been newly developed for the integrated modeling framework. The structure of EleMod is based on the MARGEN model (Pérez-Arriaga and Meseguer, 1997; Meseguer et al., 1995), a large-scale generation expansion power system tool that has been extensively used to analyze the Spanish power system, in particular, to understand generation cost recovery by means of wholesale marginal electricity prices. Similar to MARGEN, EleMod is a linear programming model that minimizes the total cost of producing electricity while considering three time ranges in the decision making process: capacity expansion planning, operation planning and dispatch. EleMod includes a limited number of conventional technologies and also intermittent wind generation. Several constraints are incorporated to have a better representation of the operation and the provision of operating reserves by the different technologies under consideration. The model preserves the hourly variability of both wind resources and electricity demand for different U.S. regions. Details about its mathematical formulation, along with a comprehensive description of the model can be found in Tapia-Ahumada and Pérez-Arriaga (2014).

Both the TD and BU models adopt a recursive-dynamic structure that —while being myopic about the future— takes into account past decisions as starting conditions to move in time. Agents base their decisions on present period variables and a sequence of optimal solutions is computed in every intra-period of two years. In USREP, a set of dynamic equations describe the evolution of capital and energy resources over time, whereas in EleMod the dynamics are given by the amount of electric capacity of conventional generation and wind technologies being installed over time, considering a linear depreciation of the existing capacity in the system based on the useful life of each technology.

3.1. Integration of USREP and EleMod models

The two sub-models are coupled via an iterative algorithm that looks for a consistent solution in both models. To integrate an electricity production model like EleMod into USREP, the latter needs some structural modifications in order to incorporate exogenous electricity generation, commodity usage (fuel, capital, labor and other materials) and CO_2 emissions. By using now a set of modified market clearing conditions, the values determined by EleMod are used to parameterize the USREP model according to the algebraic formulation already outlined by Lanz and Rausch (2011). This section focuses on the implementation of this iterative procedure, with emphasis on the incorporation of demand response into the BU model.

The *first step* requires having consistency of the initial dataset for the base year. Benchmark agreement is achieved if the inputs and outputs of the BU electricity model, over all regions and technologies, are equivalent with the aggregate representation of the electricity sector in the economic Social Accounting Matrix (SAM) data that underlies the TD model. In benchmark $m = 0$ and based on historical prices $p_{\mathrm{r,n}}^{\mathrm{fuel(0)}}$ for each fuel n, electricity demands $q_{\mathrm{r}}^{\mathrm{ele(0)}}$ and variable O&M prices $p_{\mathrm{r}}^{\mathrm{vom(0)}}$, the electricity sector model computes the optimal expansion and operation of the sector for every region r. The EleMod model determines, among other results, the annual average load-weighted price $p_{\mathrm{t,r}}^{\mathrm{elemod(0)}}$ from the hourly wholesale electricity prices and the aggregated generation output $q_{\mathrm{t,r}}^{\mathrm{elemod(0)}}$, which by construction, is equal to $q_{\mathrm{t,r}}^{\mathrm{ele(0)}}$ in the benchmark. This step ensures that, in the absence of any policy shock, the iteration between both models converges toward the base year initial conditions.

The *next step* is to parameterize the TD model using the BU solution from the benchmark (see Figure 2). In iteration $m \geq 0$, USREP simulates the rest of the economy based on regional information of the electricity sector obtained from the last known EleMod solve (i.e. benchmark $m = 0$), including the aggregated generation supply $q_{\mathrm{t,r}}^{\mathrm{ele(0)}}$, annual CO_2 emissions $em_{\mathrm{t,r}}^{\mathrm{elemod(0)}}$, capital expenditures in generating technologies $k_{\mathrm{t,r}}^{\mathrm{elemod(0)}}$, fuel expenditures $s_{\mathrm{t,r,n}}^{\mathrm{elemod(0)}}$, and variable O&M expenditures shared out across labor, materials, services and other components. Based on this information, the TD model is solved. This results in a set of solutions that include the values for elasticity $\varepsilon_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$, demand $q_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$ and price $p_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$, in addition to fuel price indexes $pi_{\mathrm{t,r,n}}^{\mathrm{fuel(m)}}$ and variable O&M price indexes $pi_{\mathrm{t,r}}^{\mathrm{vom(m)}}$.

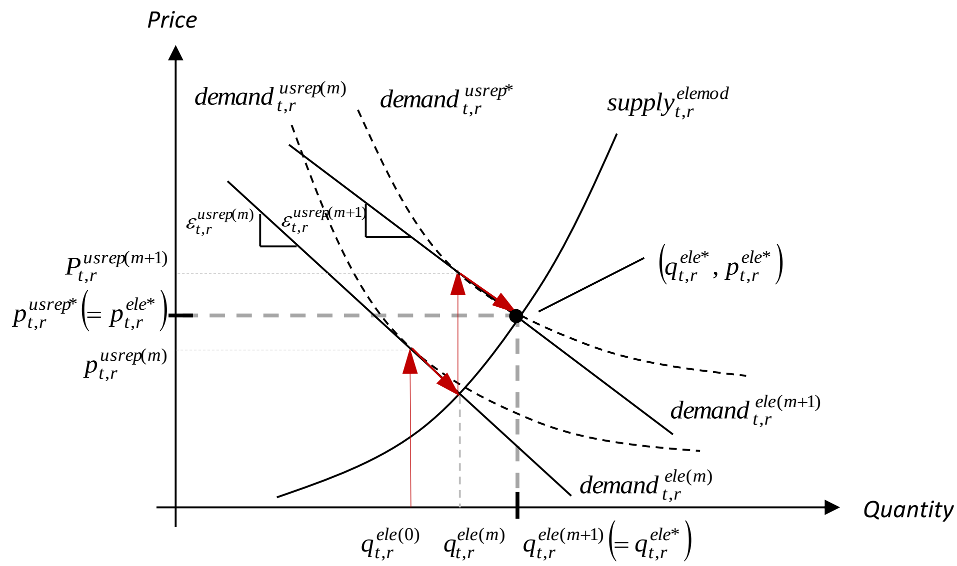

Figure 2: Iterative methodology of the integrated model approach.

The solution derived from USREP is now used to solve EleMod by updating input prices and by linearizing the demand curve. Input prices for fuels and variable O&M are updated with the corresponding price indexes according to (13)-(14).

$$p_{\mathrm{t,r,n}}^{\mathrm{fuel(m)}} = p_{\mathrm{r,n}}^{\mathrm{fuel(0)}} pi_{\mathrm{t,r,n}}^{\mathrm{fuel(m)}}, \quad \forall t, r, n \tag{13}$$

$$p_{\mathrm{t,r,n}}^{\mathrm{vom(m)}} = p_{\mathrm{r,n}}^{\mathrm{voml(0)}} pi_{\mathrm{t,r,n}}^{\mathrm{vom(m)}}, \quad \forall t, r, n \tag{14}$$

As seen in Figure 2, the electricity demand from the TD model is non-linear. In order to incorporate demand response within the supply production model, EleMod approximates the USREP demand curve with a linear function locally calibrated around the USREP solution according to:

$$p_{\mathrm{t,r}}^{\mathrm{ele(m)}} = p_{\mathrm{r,n}}^{\mathrm{usrep(m)}} + \varepsilon_{\mathrm{r,n}}^{\mathrm{usrep(m)}} \left(q_{\mathrm{t,r}}^{\mathrm{ele(m)}} - q_{\mathrm{t,r}}^{\mathrm{usrep(m)}} \right), \quad \forall t, r \tag{15}$$

where $\varepsilon_{\mathrm{t,r}}^{\mathrm{usrep(m)}} < 0$ is the local price elasticity of demand in iteration m.

The solution of EleMod with demand response results in new values for $q_{\mathrm{t,r}}^{\mathrm{ele(m)}}$, $em_{\mathrm{t,r}}^{\mathrm{elemod(m)}}$, $k_{\mathrm{t,r}}^{\mathrm{elemod(m)}}$ and $s_{\mathrm{t,r,n}}^{\mathrm{elemod(m)}}$, which are passed to USREP for the next iteration. The iterative algorithm ends when the price $p_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$ of iteration m is close enough to the price $p_{\mathrm{t,r}}^{\mathrm{usrep(m+1)}}$ of iteration $m+1$. At this point, convergence in year t for region r is reached, with a final solution given by the pair ($q_{\mathrm{t,r}}^{\mathrm{ele*}}$,$p_{\mathrm{t,r}}^{\mathrm{usrep*}}$).

However, the incorporation of demand response into the BU model is not straightforward. Ideally, maximizing the sum of consumer and producer surpluses would yield an optimal set of operating and investment decisions (Rausch and Mowers, 2013). Since the formulation of EleMod works with an objective function that minimizes total annual production costs that meets a given level of demand —including the possibility of non-served demand at a prescribed high variable cost per kWh— in each hour, another approach is required. As Figure 3 shows, an additional iterative method is implemented only within the EleMod model.

Let v denote a sub-iteration within iteration m:

1. For *sub-iteration v*, EleMod is solved for the known values of annual electricity demand $q_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$ and price $p_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$ passed by USREP. Electricity prices $p_{\mathrm{t,r}}^{\mathrm{elemod(m,v)}}$ are then estimated for each one of the regions and then compared to $p_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$. The difference $\Delta p_{\mathrm{t,r}}^{\mathrm{(m,v)}} = p_{\mathrm{t,r}}^{\mathrm{usrep(m)}} - p_{\mathrm{t,r}}^{\mathrm{elemod(m,v)}}$ is calculated. If $\left|\Delta p_{\mathrm{t,r}}^{\mathrm{(m,v)}}\right|$ is small, then the solution found by EleMod is deemed optimal. Otherwise, the electricity demand $q_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$ is increased by an amount $\Delta q_{\mathrm{t,r}}^{\mathrm{(m,v)}}$ if $\Delta p_{\mathrm{t,r}}^{\mathrm{(m,v)}} > 0$ (or decreased if $\Delta p_{\mathrm{t,r}}^{\mathrm{(m,v)}} < 0$).
2. For *sub-iteration* $v+1$, EleMod is run taking now the modified demand $q_{\mathrm{t,r}}^{\mathrm{ele(m,v+1)}} = q_{\mathrm{t,r}}^{\mathrm{usrep(m)}} + \Delta q_{\mathrm{t,r}}^{\mathrm{(m,v)}}$. New electricity prices $p_{\mathrm{t,r}}^{\mathrm{elemod(m,v+1)}}$ are calculated. Using equation (15), it is possible to approximate the USREP demand curve to a linear demand function and obtain $q_{\mathrm{t,r}}^{\mathrm{elemod(m,v+1)}}$ and price $p_{\mathrm{t,r}}^{\mathrm{ele(m,v+1)}}$ along the line. Then, the difference $\Delta p_{\mathrm{t,r}}^{\mathrm{(m,v+1)}} = p_{\mathrm{t,r}}^{\mathrm{ele(m,v+1)}} - p_{\mathrm{t,r}}^{\mathrm{elemod(m,v+1)}}$ is calculated and assessed to decide whether the value is small enough. The process that follows is the same as described above.

The sub-iteration stops when $\left|\Delta p_{\mathrm{t,r}}^{\mathrm{(m,v*)}}\right|$ is satisfactorily small in iteration $v*$, indicating that the price of the approximate demand function is close enough to the price calculated by of the supply function. Finally, iteration m of the USREP-EleMod algorithm is complete.

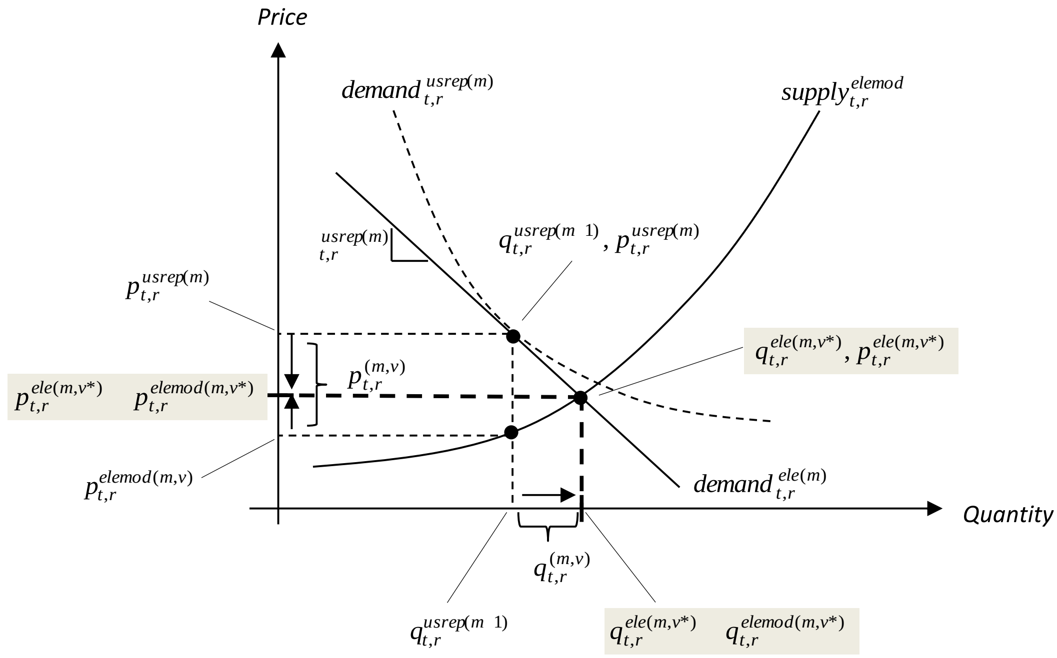

Figure 3: Incorporation of demand response within the BU electricity model.

The optimum solutions[13] $q_{\mathrm{t,r}}^{\mathrm{ele(m,v^*)}}$, $em_{\mathrm{t,r}}^{\mathrm{ele(m,v^*)}}$, $k_{\mathrm{t,r}}^{\mathrm{ele(m,v^*)}}$ and $s_{\mathrm{t,r,n}}^{\mathrm{ele(m,v^*)}}$ derived from the last EleMod run are then passed to USREP to carry out the next iteration $m + 1$.

3.2. Implementation challenges of integrated approach

Several complexities arise when integrating both TD and BU models. Since USREP is defined on an annual basis and EleMod is characterized by hourly loads and generation profiles, it is required to reconcile the time scale. The annual electricity demand $q_{\mathrm{t,r}}^{\mathrm{usrep(m)}}$ is scaled across each hour of the year according to hourly factors obtained from regional historical electricity demands taken from the initial dataset provided by the National Energy Renewable Laboratory (NREL). The optimization in EleMod is thus done for each hour and each region in order to capture geographic and temporal characteristics. Results are then aggregated and passed back to USREP.

In addition, electricity prices constitute a major linkage between the USREP model and the electric power sector model. By minimizing total electricity production costs, EleMod yields optimal economic signals that are later used to remunerate each one of the generators. Based on the economic marginal principles in electric power systems put forward by Pérez-Arriaga (1994), separate marginal prices are calculated not only for the wholesale supply of energy in the short-term, but also for the provision of guarantee of supply in the long-term and operating reserves. The Lagrangian multipliers associated to each constraint —when active— result in the prices that consumers should pay to remunerate the agents within the system who provide energy supply, upward and downward operating reserves, and available installed capacity (Tapia-Ahumada and Pérez-Arriaga, 2014).

[13] Once the optimum solution is found within the sub-iteration, v^* is dropped from the notations for simplicity.

As a result, four prices are calculated separately: *energy production price* ($\rho_{\text{t,h,r}}$), *upward operating reserve price* ($\sigma^{\text{UP}}_{\text{t,j,r}}$), *downward operating reserve price* ($\sigma^{\text{DW}}_{\text{t,j,r}}$), and *capacity reserve price* ($\tau_{\text{t,r}}$). Each of these prices are then used to estimate the annual average regional prices $p^{\text{elemod(m)}}_{\text{t,r}}$ according to:

$$p^{\text{elemod(m)}}_{t,r} = \frac{1}{\sum_h \mathrm{d}_{t,h,r}} \left(\sum_h (\rho_{t,h,r}\, \mathrm{d}_{t,h,r}) + \sum_{h\in j} \left(\sigma^{UP}_{t,j,r}\, \mathrm{OR}^{UP}_{t,j,r} \right) + \sum_{h\in j} \left(\sigma^{DW}_{t,j,r}\, \mathrm{OR}^{DW}_{t,j,r} \right) + (\tau_{t,r}\, \mathrm{MR}_{t,r}) \right) \quad (16)$$

where the hourly regional demand is given by $d_{\text{t,h,r}}$, the level of daily upward and downward operating reserve is given by $OR^{\text{UP}}_{\text{t,j,r}}$ and $OR^{\text{DW}}_{\text{t,j,r}}$ respectively, and the long-term guarantee of supply is given by $MR_{\text{t,r}}$ for region r in year t. These annual prices are then used in every iteration m of the previously described algorithm.

Finally, to achieve consistency between the electricity price calculated by USREP $p^{\text{usrep(m)}}_{\text{t,r}}$ at retail level and the calculated electricity price $p^{\text{elemod(m)}}_{\text{t,r}}$ at wholesale level, a distribution markup is estimated for each region based on the difference between the prices. Following the approach implemented by Rausch and Mowers (2013), these regional markups are calculated only for the initial benchmark iteration $m = 0$ of the base year and held constant for the rest of the iterations. The estimated values, in absolute terms, are then added back to the wholesale price —calculated by EleMod— in order to get the complete retail electricity price.

4. Asessing the suitability of a TD aproach to modeling intermittent wind energy

This section explores the evolution of an electricity system over time using both the integrated model and the TD version of the USREP model under conditions leading to a large presence of wind generation. The aim of the simulations is twofold. First, to investigate whether the models can capture wind grid-parity at wholesale level. Second, to assess the robustness of the TD approach to changes in the parameters that characterize wind generation.

4.1. Wind grid-parity

Grid-parity is the concept normally used to indicate the moment when renewable energy becomes cost competitive with the price of electricity coming from the grid, either at the wholesale or retail levels. As investments in renewables grow, it is expected that economies of scale and innovations through the process of learning by doing, as well as improvements achieved by research, will drive their cost down. Simultaneously, due to resource depletion and increasing demand, the price of fossil fuels is expected to increase driving the price of electricity up. This downward sloping cost curve of renewables and the upward sloping price curve of electricity will intersect at some price and at the connection point of the end consumers, thus defining the grid-parity point (Hurtado Muñoz et al., 2014). Reaching this point is often considered a milestone for renewables as it is believed that, once they reach it, they will dominate the market. In fact, many subsidies aimed at these technologies are sometimes justified on the basis of renewables reaching grid-parity (Lund, 2011).

By large, cost-competitiveness of renewables has been assessed using their average cost of electricity. This rather simplistic metric does, however, not capture the effects of renewable penetration into the electric power systems, such as increased volatility and depressed values of the market prices in the short-term[14] (Newbery, 2010; O'Mahoney and Denny, 2011; Sensfuß et al., 2008; Woo et al., 2011; Pérez-Arriaga and Batlle, 2012; Würzburg et al., 2013). Accordingly, the competitiveness of these technologies should be assessed on the basis of the specific energy that renewables displace at each level of penetration and the effective capacity that they can provide to the system for reliability purposes (Olson and Jones, 2012; Traber and Kemfert, 2011; Steggals et al., 2011). Doing so will allow to understand the natural limits within electricity systems that may constrain the market size of these technologies.

The numerical analysis below thus focuses on the competitiveness of wind within an electricity system from years 2006 to 2050 using the two rather sophisticated tools described in the paper: the integrated model with an exogenous BU representation of the electric power sector, and the USREP model with a detailed TD representation of the electricity generation with wind. First, a baseline scenario is constructed in the integrated model, where a decreasing cost path trajectory for wind technology is adopted with respect to a reference value[15] ($203/kW-year from 2006 to 2008, and $170/kW-year from 2010 to 2050)[16]. Second, a scenario is constructed in USREP that approximately replicates the outcomes of the integrated model. In both cases, neither renewables energy mandate nor carbon emission policy is implemented. Even though both models work with 12 U.S. regions, for simplicity results are shown only for the New England region.

4.1.1. Results from the integrated "benchmark" model

The evolution of the energy mix over time is displayed in Figure 4a. From 2010 to 2050, wind increases from 8% to 39% in terms of total electricity generation (10% to 38% in terms of installed capacity, shown in *Appendix B*). Clearly, the penetration of wind critically depends on the cost assumptions, where the relatively high costs during the first years represent a barrier for the deployment of wind. Once technology costs decrease by year 2010, it is seen a big leap in wind generation until 2016, followed by a weak development from 2018 to 2028, and ending with a steady growth from 2030 until 2050. The electricity from wind replaces the energy coming from technologies that are being retired over time, primarily nuclear and old coal steam without emissions control systems.

In the absence of any carbon emission policy or renewable portfolio standard, the baseline case shows an increment of CO_2 emissions until 2028, after which emissions decrease up to 62

[14]This is the so called merit-order effect, which is the result of adding renewable energy to the market at lower marginal costs while displacing generation from conventional plants with higher marginal costs.

[15]The baseline case considers a reference value of $169.133/kW-year. This annualized fixed cost is the sum of capital cost and fixed O&M for onshore wind technologies, considering an evaluation period of 20 years and a discount rate of 7%. Most of the economic and technical parameters used in the EleMod model are based on values used by NREL's ReEDS model as of year 2011.

[16]In addition, several simplifications have been adopted to observe more neatly the penetration of wind over time. First, a simple cost learning curve for wind is assumed. Second, only one wind technology class has been included in the simulation runs. Third, regional wind resource or available wind capacity is unlimited for this particular class of wind.

$MMTCO_2$ in 2050 or, equivalently, 20% above the emission level of year 2006 (Figure 5a). It can be seen that the deployment of wind after 2028 helps to stabilize emissions coming from the growing electricity production of fossil-fuelled conventional technologies, mostly gas and coal-fired power plants.

The electricity prices for the region experiment a 20% or $27/MWh increase over a period of 44 years (Figure 5b), as a consequence of greater electric demand and more expensive fuels. In fact, coal prices show a more than twofold increase and natural gas prices a 57% increment by 2050 relative to year 2006. Although wind technology is competitive, fossil-based generation is still widely used in this scenario, with over 60% of the total electricity generation coming from coal and natural gas by the end of the period. *Appendix B* shows the complete set of results of the integrated model for the electricity sector in New England.

4.1.2. Results from the TD approach

This section explores the evolution of the electricity system using the TD version of USREP. The numerical simulations were conducted using the wind technology specification as described in Section 2. The assumptions for this scenario include a combination of parameters for which the penetration pattern of wind roughly approaches the results from the integrated model, i.e. mark-up parameter $\mu_n = 0.885$ (see Eq. 2) and an initial fixed factor endowment $inish = 0.0002$ (see Eq.11) for wind technologies.

As Figure 4b displays, wind increases its penetration in the system until it reaches 39% of the total generation by year 2050. This technology does not overtake the market even when being competitive with markup $\mu < 1$, because its penetration is controlled by the fixed factor input requirement which has been initialized with a small endowment (and subsequently growing over time as a function of the penetration of wind in the system). Although the trajectory is different from the integrated model results, the participation of wind in the energy mix is the same by the end of the time horizon. Comparing emissions shows that, given that the energy mix in the TD case includes hydro resources, absolute CO_2 emissions are lower than in the integrated case and with a downward trend because of the growing penetration of wind (Figure 5a). Retail electricity prices in both cases are quite close until year 2030, after which wind becomes more important within the energy mix and prices deflate (Figure 5b).

Summing up, we then conclude that *if a well-informed parametrization is used in the TD approach that is based on prior results from the integrated model, the TD approach is capable of roughly replicating the evolution of the electricity sector with a strong presence of wind*. Arguably, researchers specifying TD models typically do not possess this kind of information *a priori*. We therefore analyze next how robust the results from the TD model are with respect to uncertainty in specifying key model parameters.

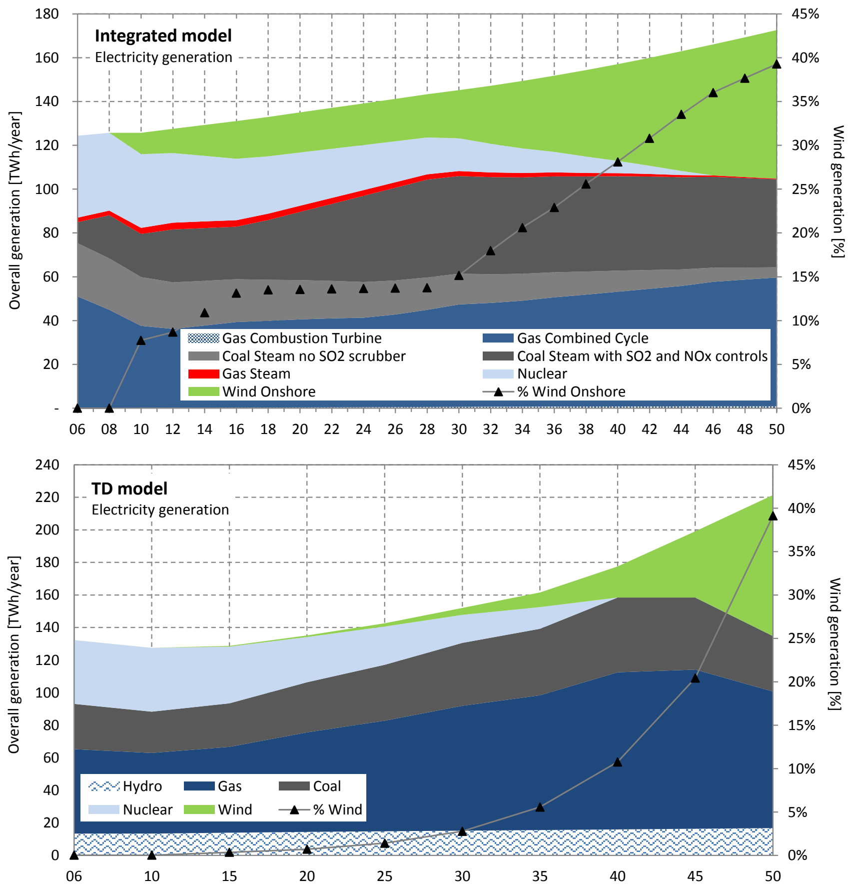

Figure 4: Electricity generation per technology from years 2006 to 2050 for New England region. Results from integrated model (a), and from TD model with mark-up=0.885 and fixed factor=0.0002 (b).

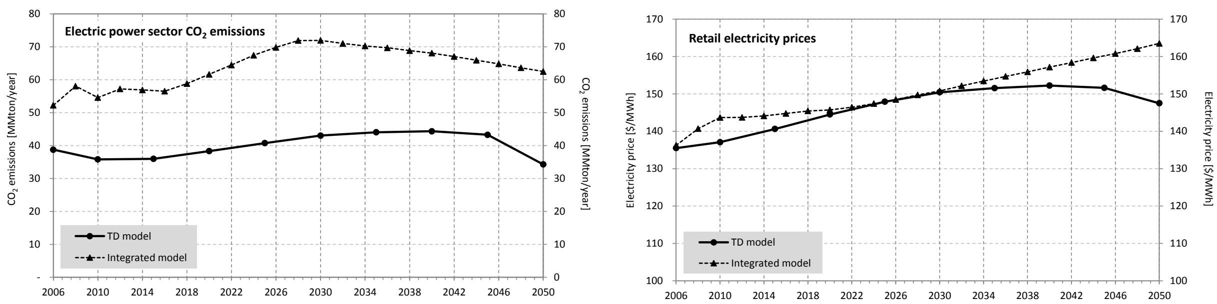

Figure 5: Electric power sector CO_2 emissions (a), and retail electricity price (b) from years 2006 to 2050 for New England region. Results for integrated model (black triangles) against TD approach with mark-up=0.885 and fixed factor=0.0002 (black circles).

4.2. *Robustness of TD approach*

Section 2 has identified the four key parameters used in the TD approach to represent the electricity sector with intermittent wind energy. To investigate the sensitivity of the TD approach, we analyze the evolution of the electricity mix for cases which vary two of these critical parameters. We focus here on the mark-up parameter and the initial fixed factor endowment.[17]

First, the mark-up parameter μ_n as seen in Eq. 2 is used to rank electricity technologies based on their incremental cost compared to the cheapest technology in the benchmark data (coal generation). If the mark-up factor for wind is assumed to be (or estimated) +5% higher than the reference value (i.e., 0.93 vs. 0.885), then electricity generation from wind will be more expensive in the model and will represent less than 2% as opposed to 39% of total electricity generation in the baseline case (see Figure 6a). Second, the initial fixed factor endowment *inish* enters Eq. Eq. 11 which allows wind technology to grow according to the behavior typically observed for new technologies. This parameter is also used to more broadly reflect institutional barriers faced by new technologies. It is typically set based on expert judgments and therefore remains largely subjective. If the initial endowment is halved (i.e., 0.0001 vs. 0.0002), then the penetration rate of wind predicted by TD approach will be significantly slower, reaching about 20% (instead of 39%) of the generation mix by 2050 (see Figure 6b).

Further analysis illustrating the range of outcome due to modest variations in either one of the parameters are shown in Figure 7. If the mark-up factor μ_n fluctuates between (0.97 - 0.78), the share of wind varies between (0% - 43%) in year 2050. If the fixed factor moves between (0.0001 - 0.0004) then the participation of wind fluctuates between (21% - 39%). In both cases, not only the final amount of wind changes but also its penetration pattern over time as seen in the figures. Results also show a wide variation in the simulated CO_2 emissions, as the carbon content of the energy mix varies with the technologies being deployed. By year 2050, the emissions of the electricity sector in New England range between -6% and +60% with respect to the reference value. See *Appendix C* for results of CO_2 emissions and electricity prices.

These analyses show that the penetration pattern in the TD approach is highly sensitive with respect to the mark-up parameter and exhibits a lesser but still significant sensitivity with respect to the fixed resource factor. For us, this seems to suggest that without the support of a BU electricity-sector model, it is difficult to find a parameterization of TD approaches—based on the current generation of TD approaches—that can reproduce correctly the penetration pattern of intermittent renewable energy and the overall electricity generation mix.

[17]We thus do not vary the nested structure for electricity generation underlying the TD model. We also do not change the substitution elasticities between the fixed resource factor and other inputs to production, $\sigma_{\mathrm{n}}^{\mathrm{FF}}$. While these do of course have an impact on the quantitative model outcomes, they have been constructed to represent physical wind resource potentials. We thus do not consider these parameters in our sensitivity analysis.

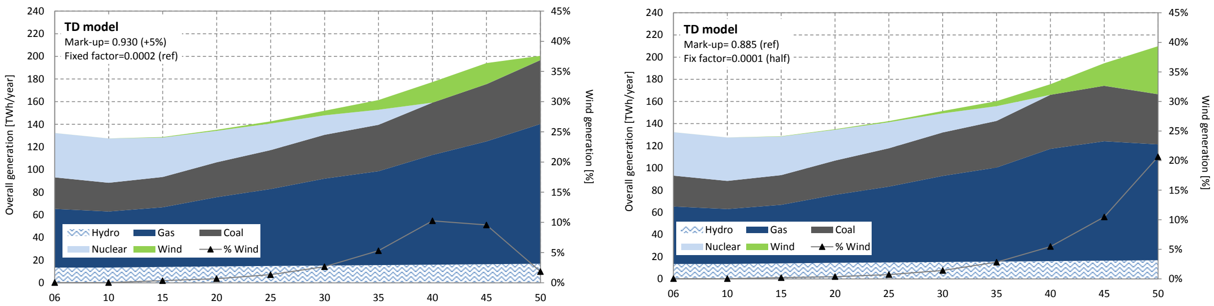

Figure 6: Electricity generation per technology from years 2006 to 2050 for New England region. Results from TD model with mark-up=0.930 (+5%) (a), and fixed factor=0.0001 (half) (b).

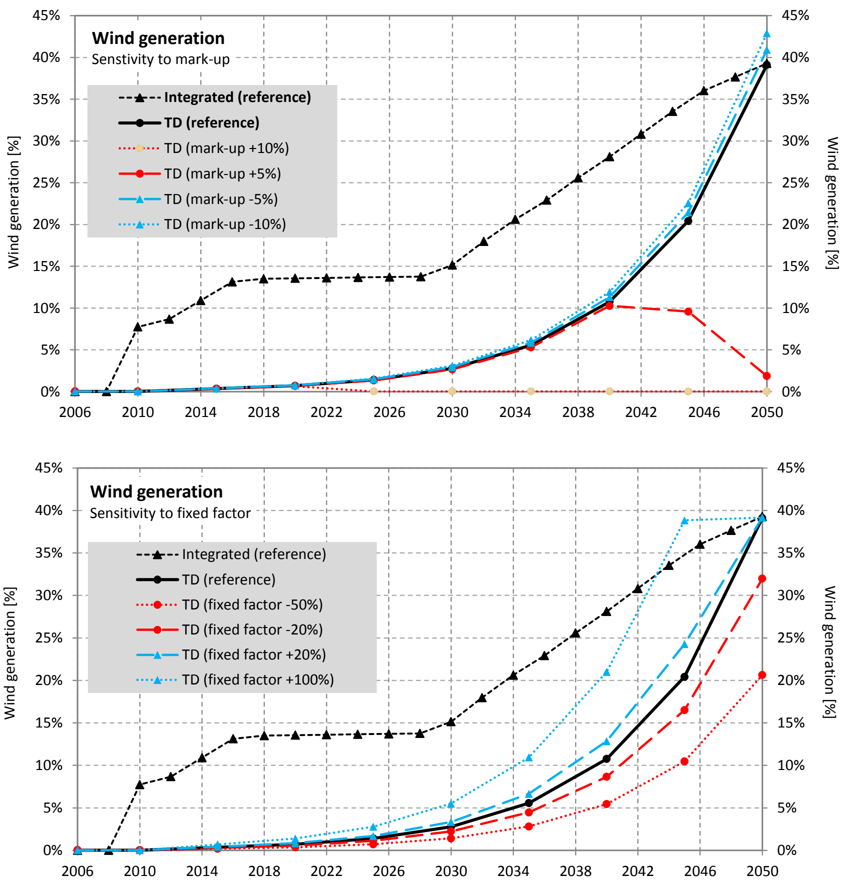

Figure 7: Wind generation as % of total generation from years 2006 to 2050. Sensitivity to mark-up factor (a), and sensitivity to fixed factor (b). Results from TD approach compared against integrated model.

4.3. Optimal equilibrium level of wind

Why does the TD approach can potentially differ so much from the integrated model? One reason is as follows. From the simulation results it is possible to observe that after wind reached grid-parity at the wholesale level, its penetration attained a natural limit and the technology did not dominate the market over time (Figure 4a). In a recursive-dynamic centralized planning model like EleMod, the different generating technologies compete in order to supply electricity (energy and reserves) at minimum cost. Optimal decisions need to consider a number of elements, such as demand temporal variation, system reliability considerations, and the individual characteristics of the generation pool available in the region. Consequently, wind becomes part of this energy portfolio mix when a combination of wind with other conventional technologies is a more cost-effective alternative than a combination without it. Results from the integrated model (Figure 8) show that—since some new capacity is added every year—wind capacity is always well-adapted in the sense that it fully recovers the costs (red triangles) through income (dotted black line) it obtains for providing energy and reserves. In addition to the remuneration for energy (light brown), wind should also be remunerated for its contribution to the system's capacity adequacy (purple), and should be charged (orange) for its responsibility in increasing the operating reserves of the system.

These observations demonstrate that in equilibrium there is an optimum amount of wind every year and that the total costs of wind production are fully recovered under properly designed market prices. These outcomes are consistent with the long-term equilibrium of an optimally adapted electric power sector as, for example, discussed by Pérez-Arriaga (1994) and more recently by Green and Vasilakos (2011). If more wind were installed, then the technology would not recover costs because of the flattening effect of wind penetration on the market prices that apply to wind production and the subsequent revenue drop in the short-term[18]. On the contrary, if less wind were installed than the optimum level, then this technology would have a revenue stream larger than its costs, giving wind investors an incentive to install more wind until eventually the optimum amount is reached. See *Appendixes D-E* for the methodology used for wind income calculations and results from numerical simulations.

It is evident that the TD approach—due to its highly aggregated structure—cannot capture these relevant features of wind generation and, more broadly, electric power systems.

[18]The decrease in revenues has a compound price and quantity effect, as now in this case a larger volume of wind energy is being traded at a lower price.

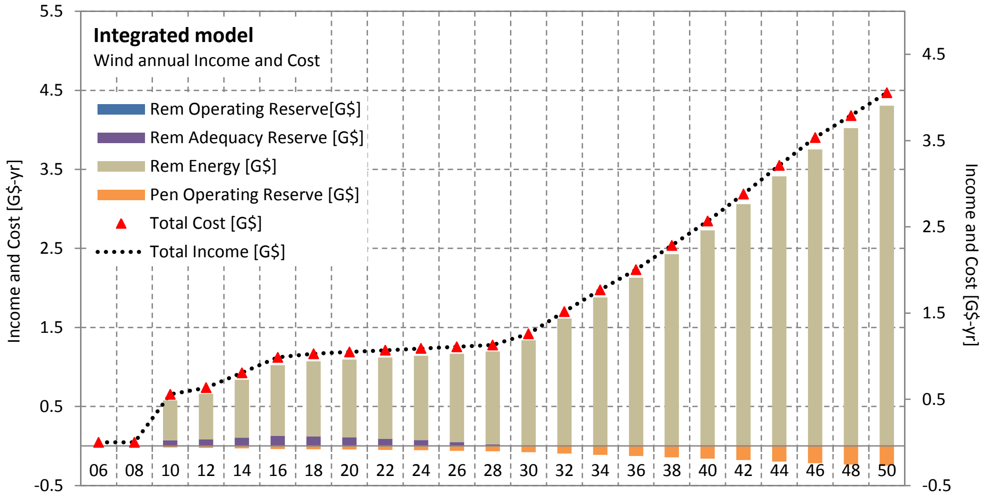

Figure 8: Total annual income and cost for wind—disaggregated by component and over time (year 2006 to 2050).

5. Concluding remarks

Top-down (TD) equilibrium models have traditionally proved to be valuable tools for assessing economy-wide climate or energy policies, including model-based simulations that pertain to the evolution of the electric power sector. New modeling challenges brought about by intermittent renewable generation require to carefully review and enhance existing modeling tools. This paper has investigated the suitability of a "current generation" TD approach to assessing the implications of high levels of intermittent wind energy for future energy systems.

To this end, it has developed an integrated economy-electricity framework that incorporates a capacity planning and economic operation model of the electric power sector within an economy-wide general equilibrium framework. This enabled creating a "benchmark" model which has been used to scrutinize the performance of a TD approach to modeling intermittent renewable energy. We have assessed the performance of the TD approach by (i) focusing on whether or not the models can capture wind grid-parity and (ii) by investigating the robustness of the TD approach to changes in the parameters that characterize wind generation. The analysis strongly suggests that without *a priori* information on key parameters of the TD approach, this approach is not capable of truthfully simulating the evolution of the electricity sector with a strong presence of wind. If adequate information is available, that is consistent with the assumed model structure, a TD approach may be able to roughly replicate the behavior of a (more) realistic bottom-up (BU) approach. While this insight may be somewhat comforting, we argue that it is not realistic that TD modelers possess this kind of information when developing such models. Moreover, our analysis has exposed significant sensitivities of the TD approach in terms of the projected evolution of wind energy and the overall electricity generation mix with respect to the key parameters in the TD approach. Using simulation-based analysis we have shown that very small variations in these critical parameters—on the order of magnitude that TD modeler would usually consider to be negligible or "non-identifiable"—are sufficient to give rise to largely disparate outcomes in the TD paradigm.

The critical parameters analyzed in the simulations encompass, in a single number, a complex ensemble of information about wind technologies, making it difficult to properly characterize their behavior within the power system. The integrated model circumvented this problem by incorporating a more canonical portrayal of the electric sector, where the system and technology assumptions are specified in a detailed fashion that is backed up by engineering knowledge. The proposed model, thus, was able to endogenously decide the most adequate level of capacity and generation for wind (and other generation technologies) over time.

Results showed that the regional electricity matrix was a balanced combination of different technologies, where wind did not dominate the market once it reached grid-parity. By looking at the profits of each technology, the integrated model prevented the installation of additional wind when total revenues equaled total costs. Although the TD approach also imposes zero profits and market clearance conditions, the outcomes obtained with the integrated model show a more realistic behavior of the electricity sector with high penetration of wind.

As renewables become crucial for reaching a low-carbon economy, they add new complexities into the energy systems. If not properly upgraded, traditional simulation tools run the risk of misrepresenting the implications of future policies. The integrated model presented in this paper offers a sound alternative to bridge the gap between the TD and BU modeling paradigms. Future research directions will address whether or not some of the key assumptions regarding the structure and parameters used in TD equilibrium (e.g., economy-energy computable general equilibrium) models can be estimated and further refined to account for the adaptation of the electric power sector to high penetration of intermittent renewable energy sources.

Acknowledgements

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Appendix A. Renewable energy representation in the TD approach

The following figures and tables present the nesting structure used for the electricity sector, the variables and parameters related to renewable electricity, and the datasets used in the top-down USREP model.

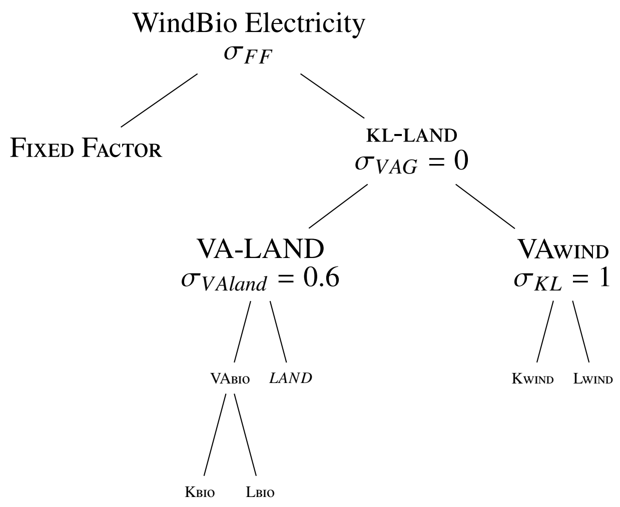


Figure A.9: USREP Nesting Structure for *windbio* generation.

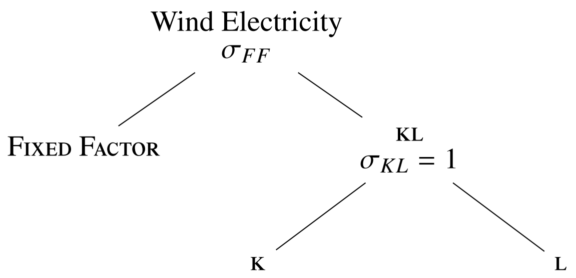


Figure A.10: USREP nesting structure for *wind* generation.

Table A.1: Variables in the equilibrium conditions related to renewable electricity TD representation (*windgas* generation)

	Level variables		Price variables
ELE^n	Electricity generation from wind technologies	P^{ELE}	Price index for electricity
ELE^{Fossil}	Electricity generation from fossil technologies	P^{FF}	Price index for fixed factor
$ELE^{Nuclear}$	Electricity generation from nuclear technology	P^{KLG}	Price index for capital-labor-gas composite for hybrid technology
ELE^{Hydro}	Electricity generation from hydropower	P^{VAwind}	Price index for value added (capita-labor) for wind
$Demand^{Ele}$	Electricity Demand	P^{VAgas}	Price index for composite value added-gas for gas turbine
K	Capital supply	P^{KL}	Price index for value added (capital-labor) for gas turbine
D^K	Capital demand from non-electricity sectors	P^K	Price index of capital
D^L	Demand for labor	P^L	Price index of labor
L	Labor	P^{gas}	Price index of gas
S^{wind}	Supply of fixed factor		
D^{ELE}	Demand for electricity		
S^{gas}	Supply of gas		
D^{gas}	Demand of gas from non-electricity sectors		

Table A.2: Parameters related to renewable electricity in TD representation (*windgas* generation)

Symbol	Name
θ^{FF}	Benchmark value share of the fixed factor
θ^{KLG}	Benchmark value share of the composite capital- labor-gas for the "synthetic" technology
θ^{VAwind}	Benchmark value share of capital-labor for wind
θ^{VAgas}	Benchmark value share of capital-labor-gas for wind turbine
θ^K_{wind}	Benchmark value of capital for wind turbine
θ^L_{wind}	Benchmark value of labor for wind generation
θ^{KLG}_{gas}	Benchmark value share of capital-labor bundle for gas turbine
θ^{gas}	Benchmark value of gas for wind back-up generation
θ^K_{gas}	Benchmark value share of capital for gas turbine
θ^L_{gas}	Benchmark value share of labor for gas turbine
σ_{FF}	Elasticity of substitution between the fixed factor and other inputs to production
σ_{KL}	Elasticity of substitution between capital and labor for wind
σ_{KLg}	Elasticity of substitution between capital and labor for gas turbine
σ_{VAG}	Elasticity of substitution between capital-labor-gas turbine and capital-labor-wind
σ_{KLG}	Elasticity of substitution between capital gas and capital-labor bundle
μ_n	Mark-up factor
$\overline{ELE}$	Benchmark value of electricity production from the different technologies
$\overline{K}$	Capital endowment in the economy
$\overline{L}$	Labor endowment in the economy
$\overline{NR}$	Natural resources endowments in the economy

Table A.3: Inputs to production shares used in wind technologies in USREP (θ_n)

	Wind	*Windbio*	*Windgas*
Capital for wind turbine	0.75	0.305	0.511
Labor for wind production	0.20	0.081	0.136
Fixed factor	0.05	0.050	0.050
Capital for bioelectricity facility backing up wind	–	0.417	––
Labor for bioelectricity facility backing up wind	–	0.130	––
Land for bioelectricity facility backing up wind	–	0.017	––
Capital for gas turbine backing up wind	–	––	0.200
Labor for gas turbine backing up wind	–	––	0.086
Natural Gas	–	––	0.017

Source: USREP model input data based on Paltsev et al. (2005a).

Table A.4: Cost assumptions for the computation of LCOE in USREP (to estimate μ_n)

	Units	Pulverized Coal	Wind	Wind Plus Biomass Backup	Wind Plus NGCC Backup
Overnight Capital Cost	$/kW	1875	1752	5183	2616
Fixed O&M	$/kW	25.1	27.3	86.1	38.0
Variable O&M	$/kWh	0.0041	0.00	0.0061	0.0018
Project Life	years	20	20	20	20
Heat Rate	BTU/kWh	8740	–	7765	6333
Fuel Cost per kWh	$/kWh	0.0087	–	0.0007	0.0028
Transmission and Distribution	$/kWh	0.02	0.02	0.03	0.03

Source: Morris et al. (2010).

Table A.5: Mark-up parameter for different wind technologies in USREP by region (μ_n)

	Wind	*Windbio*	*Windgas*
Alaska	1.0	2.7	1.3
California	1.1	2.8	1.4
Florida	1.2	3.3	1.6
New York	1.3	3.3	1.7
Texas	1.0	2.7	1.4
New England	1.3	3.2	1.6
South East	1.2	3.3	1.6
North East	1.1	3.2	1.4
South Central	1.1	3.0	1.5
North Central	1.1	2.9	1.4
Mountain	1.0	2.6	1.3
Pacific	1.0	2.7	1.3

Source: USREP model input data computed based on NREL Wind Resource Data and Morris et al. (2010), as explained in Rausch et al. (2010,2011).

Appendix B. Electricity sector results of the integrated model

Appendix B.1. Wind energy and capacity deployment

Figure B.11 displays a continuous deployment of wind technology over time. From 2010 to 2050, wind increases from 10% to 38% in terms of installed capacity (Figure B.11a), and from 8% to 39% in terms of total electricity generation (FigureB.11b). Clearly, the penetration of wind is assisted by the cost assumptions adopted for the baseline case, where the relatively high costs during the first years represent a barrier for the deployment of wind. Once technology costs decrease by year 2010, it is seen a big leap in wind installed capacity until 2016, followed by a weak development from 2018 to 2026, and ending with a steady growth from 2028 until 2050. Also, as Figure B.11c shows, the electricity from wind replaces the energy coming from technologies that are being removed over time, primarily nuclear and coal steam without emissions control systems.

In the absence of any carbon emission policy or renewable portfolio standard, the baseline case shows an increment of CO_2 emissions until 2028, after which emissions decrease up to 62 $MMTCO_2$ in 2050 or, equivalently, 20% above the emission level of year 2006 (Figure B.11b). It can be seen that the deployment of wind after 2028 helps to stabilize emissions coming from the growing electricity production of fossil-fuelled conventional technologies, mostly gas and coal-fired power plants. However, it is not enough to reduce emissions in the electric power sector over time, which by the end of 2050 contributes to 43% of the total U.S. energy-related CO_2 emissions, above the estimated 39% of the initial year 2006 (not reported here).

Looking at the electric capacity portfolio mix (Figure B.11a and Figure B.12a), it can be seen that, as wind increases in capacity, gas technologies experiment a considerable increase of their installed capacity. While nuclear, gas steam and old coal steam technologies are withdrawn for the market, the penetration of wind is supported with the installation of gas turbines and combined cycles as well as coal steam with emissions control systems. In fact, their contribution for the long-term guarantee of supply seems to become quite relevant under the presence of large amounts of wind. As Figure B.12b displays, open cycle gas combustion turbines are mostly used for backup purposes, having very low capacity factors of less than 1% during the entire time horizon. In the case of combined cycles, their annual capacity factors decrease over time, from 53% in 2006 to less than 35% in 2050.

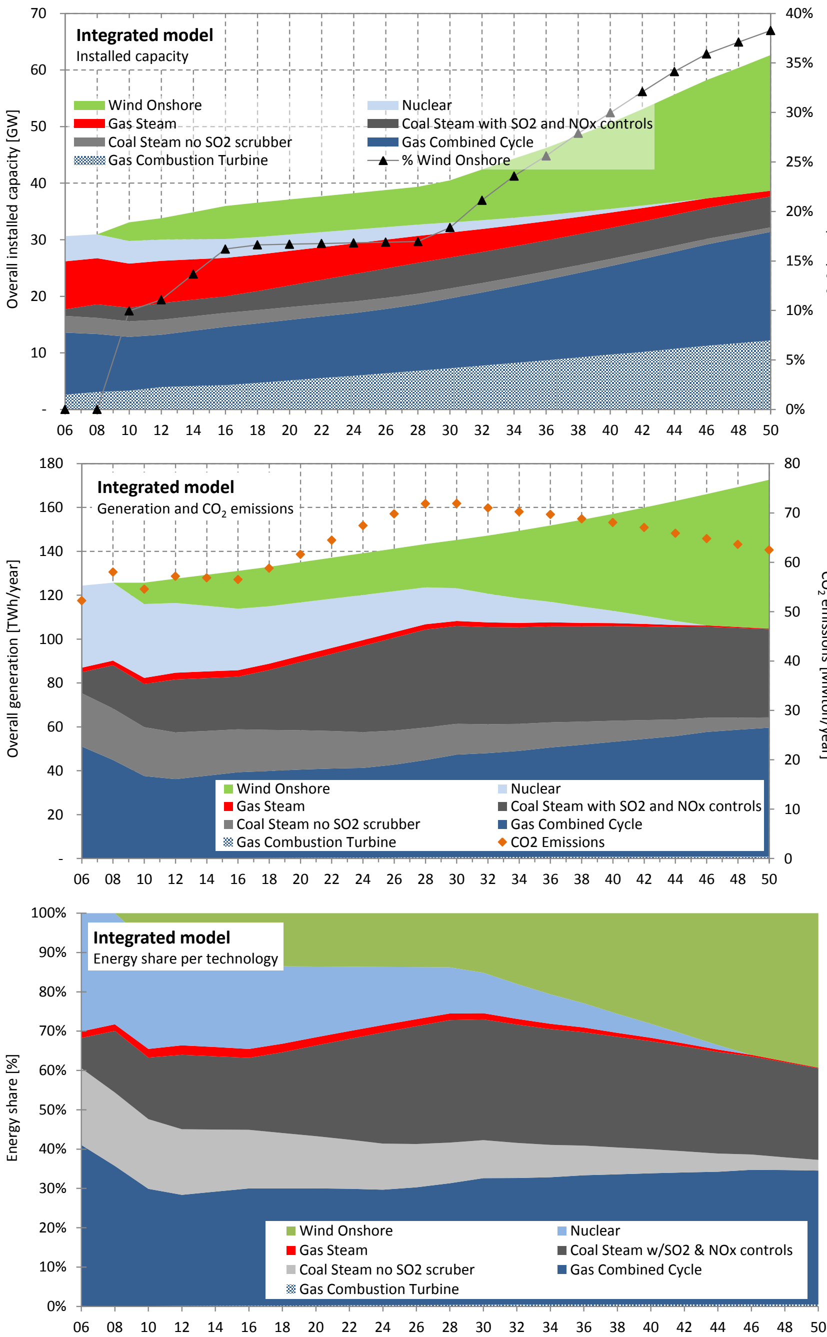


Figure B.11: Cumulative installed capacity and % of wind over total installed capacity (a), electricity generation and regional CO_2 emissions (b), and electricity portfolio share per technology (c) from years 2006 to 2050.

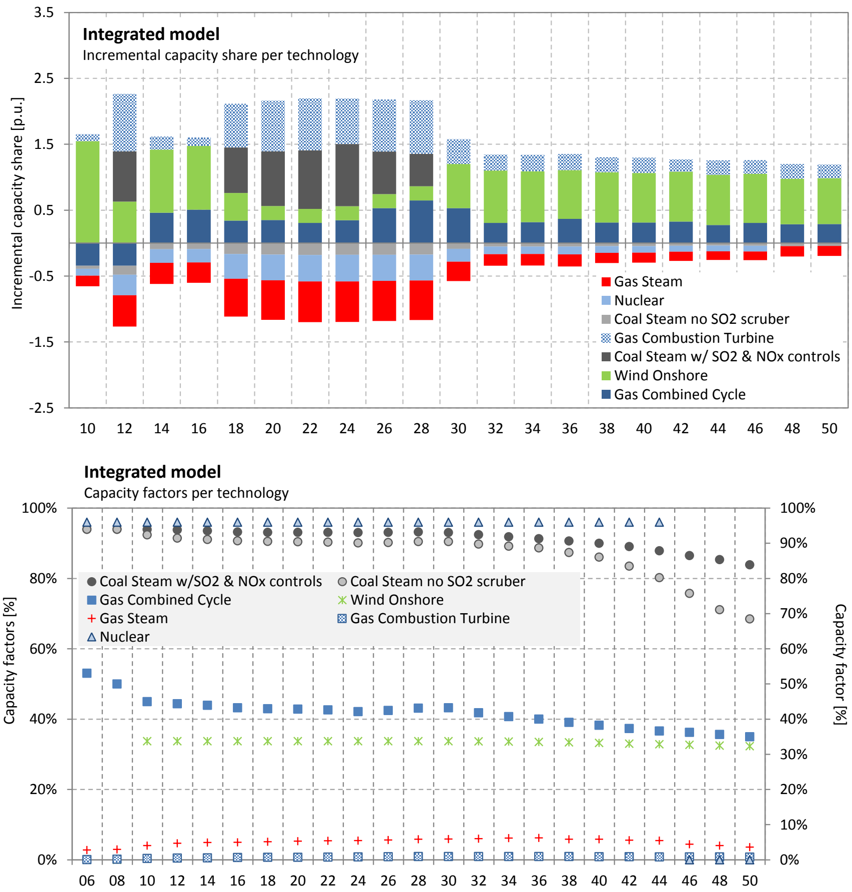


Figure B.12: Annual incremental capacity share (a) and annual capacity factor (b) by technology type over time.

Finally, the baseline scenario suggests a low contribution of wind to generation adequacy (i.e. a given margin of installed firm generation capacity over estimated peak demand), especially under very large penetration for the New England region. Figure B.13a shows that although wind capacity increases substantially, the amount of firm capacity by conventional technologies above the system's peak demand remains almost constant over time. In fact, looking at the contribution of wind during the peak hours of each year, it is possible to calculate its capacity credit per unit of installed capacity[19]. Results show that capacity credit decreases over time, with a value of 13% by 2050 compared to 17% in 2010 (Figure B.13b). Results also show that the capacity credit of wind decreases as cumulative capacity increases over time (Figure B.13c), indicating that its incremental contribution to security of supply decreases.

[19]Wind capacity credit is assessed as the ratio of the average wind electricity generation during the 100 peak-hours of every year to the cumulative wind installed capacity up until the year being analyzed. This value represents the contribution of wind to meet peak demand or, equivalently, the reduction in the amount of capacity of other technologies.

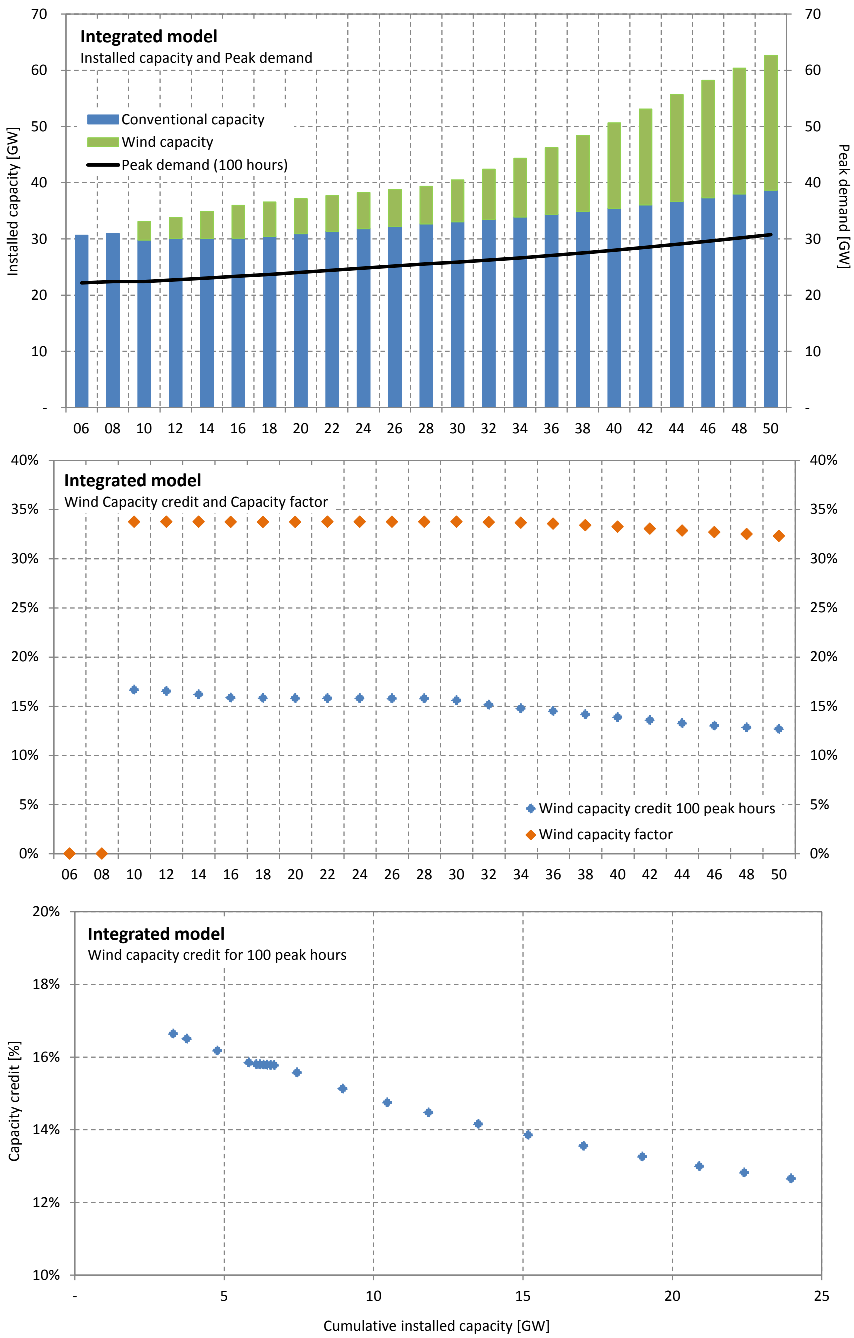


Figure B.13: Installed capacity and average peak demand over 100 peak-hours over time (a), wind capacity credit over 100 peak-hours over time (b), and wind capacity credit as a function of installed capacity (c).

Appendix B.2. Fuel and electricity prices growth

Another set of results from the integrated model is the regional evolution of fuel and electricity prices over time (Figure B.14). According to the model, the electricity price for the New England region experiments a 20% or $27/MWh increase over a period of 46 years as a consequence of greater electric demand and more expensive fuels. In fact, coal prices show a more than twofold increase and natural gas prices a 57% increment by 2050 relative to year 2006. Although wind technology is competitive, fossil-based generation is still widely used in this scenario, with over 60% of the total electricity generation coming from coal and natural gas by the end of the period (see Figure B.11c above).

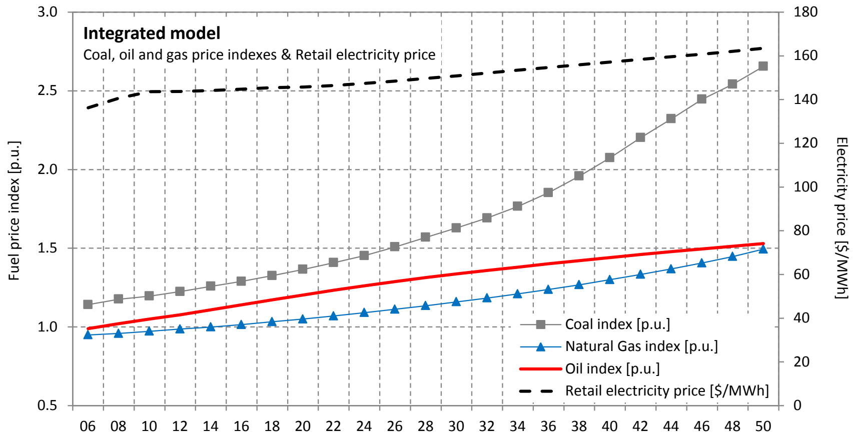


Figure B.14: Fuel index price and retail electricity price from year 2006 to 2050.

Appendix C. Sensitivity analyses of top-down USREP model

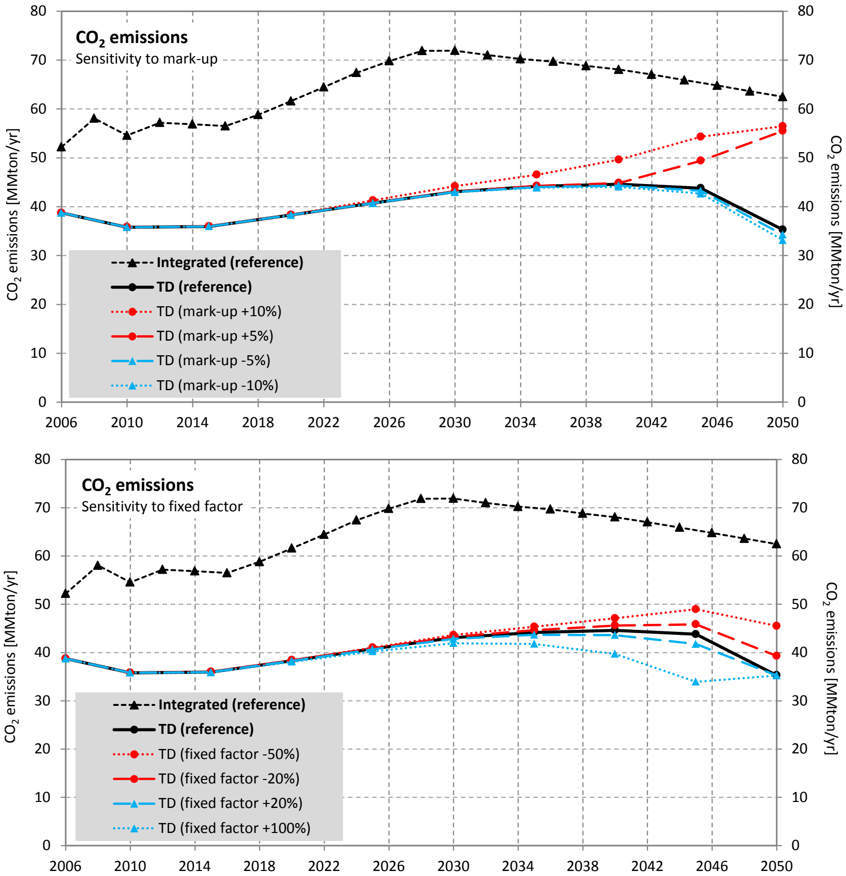


Figure C.15: CO_2 emissions of electricity sector from years 2006 to 2050 for New England region. Sensitivity to mark-up factor (a), and sensitivity to fixed factor (b). Results from TD version compared to integrated model results.

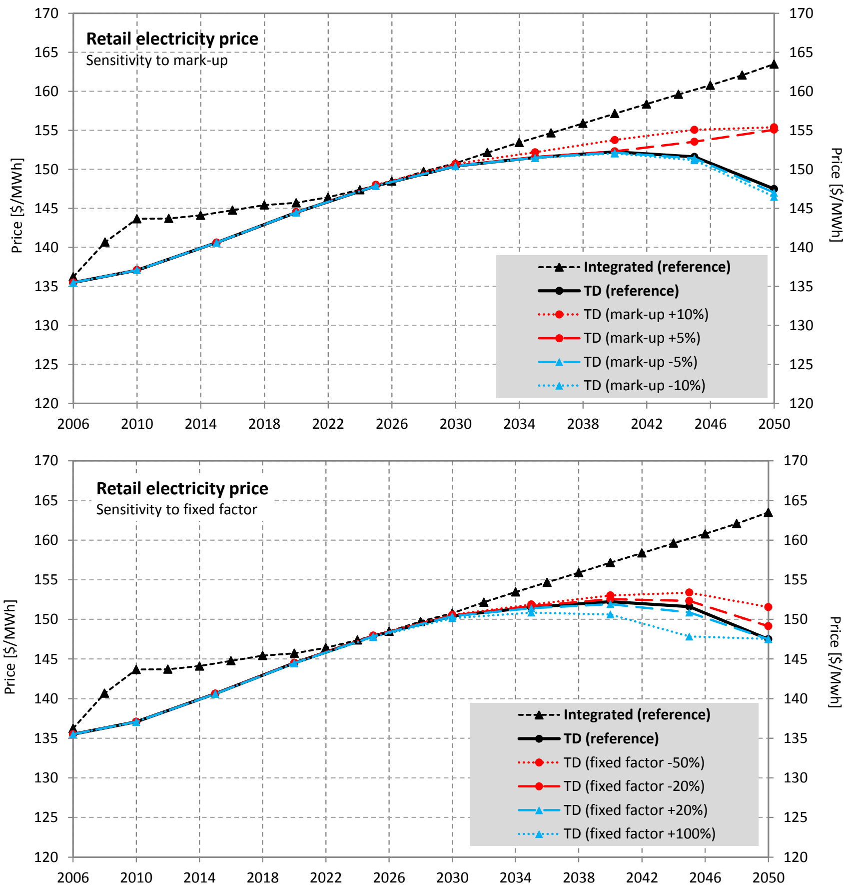


Figure C.16: Retail electricity prices from years 2006 to 2050 for New England region. Sensitivity to mark-up factor (a), and sensitivity to fixed factor (b). Results from TD version compared to integrated model results.

Appendix D. Wind technology income and cost trajectory over time

The analysis also looked into the income (and cost) that wind technology accrues annually over time (Tapia-Ahumada and Pérez-Arriaga, 2014). Regarding costs, EleMod uses a simple cost path trajectory for wind technology with an annualized fixed cost for every year. This value is estimated as the sum of capital cost and fixed O&M for onshore wind technologies, considering an evaluation period of 20 years and a discount rate of 7%. As to revenues, EleMod calculates them based on four separate regional marginal prices that consumers pay for the provision of electricity, including an energy production price ($\rho_{t,h,r}$), a downward operating reserve price ($\sigma^{DW}_{t,h,r}$), and a capacity reserve ($\tau_{t,r}$) price. Thus, wind electricity supply is remunerated through several components:

1. *Wholesale energy sales*, given by the annual sum of the hourly energy price $\rho_{\mathrm{t,h,r}}$ times the amount of power generated by wind $vGw_{t,h,r,c}$ per class c, region r and year t:

$$\mathrm{REMw}^{\mathrm{energy}}_{t,r,c} = \sum_{h} \left(\rho_{t,h,r} * \mathrm{vGw}_{t,h,r,c}\right), \quad \forall t, r, c \tag{D.1}$$

2. *Contribution to downward operating reserves*, calculated as the annual sum of the contribution of wind to downward reserves $vGw_{t,h,r,c}$ times the associated price $\sigma^{\mathrm{DW}}_{\mathrm{t,j,r}}$ at the hour h of the day j when reserve requirements are needed. Wind technology is assumed to be fully flexible, i.e. without a minimum load specification. The amount of reserve is defined on a daily basis, considering unexpected short-term variations of electricity demand and wind production:

$$\mathrm{REMw}^{\mathrm{OR}}_{t,r,c} = \sum_{j,h\in j} \left(\sigma^{\mathrm{DW}}_{t,j,h,r} * \mathrm{vGw}_{t,h,r,c}\right), \quad \forall t, r, c \tag{D.2}$$

3. *Contribution to long-term capacity reserve*, given by the generation capacity reserve price $\tau_{\mathrm{t,r}}$ times the contribution of wind to total firm capacity. This amount is estimated considering the installed capacity of wind $\hat{K}w^{\mathrm{cumulative}}_{t,r,c}$ up until year t and its average availability given by its projected capacity factor $f^{\mathrm{availability}}_{r,c}$. The amount of reserve for resource adequacy is defined as a predetermined margin over the peak load of the region:

$$\mathrm{REMw}^{\mathrm{MR}}_{t,r,c} = \left(\tau_{t,r} * \hat{K}\mathrm{w}^{cumulative}_{t,r,c} * \mathrm{f}^{\,availability}_{\,r,c}\right), \quad \forall t, r, c \tag{D.3}$$

The intermittency of wind requires a flexible response of the power system, including making use of operating reserves, the use of advanced wind forecasting techniques and some changes in market rules to shorten the scheduling times NERC (2009). Experience shows that large deviations in predictions of wind output can occur both in magnitude and timing. Load predictions made 24-36 hours ahead are fairly accurate. This is not true for wind predictions. While the error for a single plant can be about 5-7% for 1- to 2-hour ahead forecasts, the error increases up to 20% for day-ahead forecasts (Milligan et al., 2009). It has been shown that that the impact of wind penetration on the requirement of reserves is strongly related to the growth of the error in the wind forecast with the distance to the real time and with higher penetrations of wind (Ela et al., 2008; Holttinen et al., 2011; EURELECTRIC, 2010).

Taking into consideration some of these elements, the EleMod model incorporates the error in day-ahead predictions of wind within the daily requirements for upward/downward operating reserves. Very simply, the model defines this error as a percentage of the maximum wind production estimated for the day $Gw^{\max}_{t,j,r,c}$. Consequently, if wind increases operating reserves, then a penalty is applied given by the upward and downward operating reserve prices ($\sigma^{\mathrm{UP}}_{t,j,h,r}$, $\sigma^{\mathrm{DW}}_{t,j,h,r}$) times the portion of wind energy contributing to that error (20% $Gw^{\max}_{t,j,r,c}$), as shown in (D.4).

$$\mathrm{PENw}^{\mathrm{OR}}_{t,r,c} = \sum_{j,h \in j} \left(20\% * \mathrm{Gw}^{\max}_{t,j,r,c} * \left(\sigma^{\mathrm{UP}}_{t,j,h,r} + \sigma^{\mathrm{DW}}_{t,j,h,r}\right)\right), \quad \forall t, r, c \tag{D.4}$$

For the New England electricity market and after considering costs, remunerations and penalty for wind prediction errors, Figure D.17 shows income and cost per unit of capacity along with cumulative installed capacity of wind over time. It is observed that wind goes through a slow expansion until 2028, followed by an almost linear growth rate until year 2050.

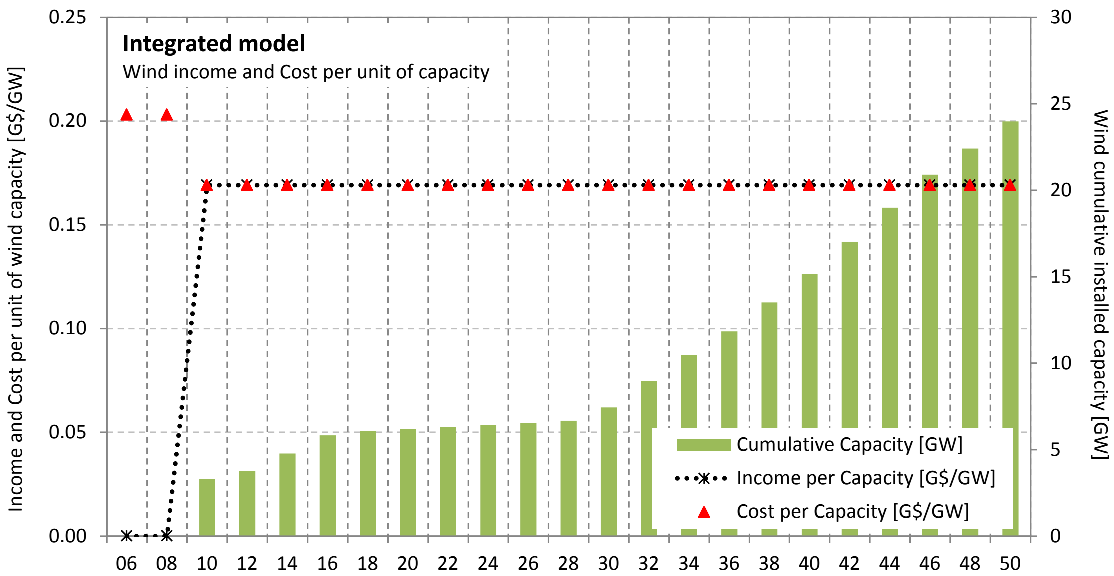


Figure D.17: Wind income and cost per unit of installed capacity, and installed capacity from year 2006 to 2050 for New England region.

Although wind becomes competitive with respect to other conventional technologies after year 2010, this technology does not dominate the market and its penetration is combined with the deployment of the other conventional generation units that complement the operation of wind. Because of the detailed representation of the electricity sector in EleMod, the integrated model is able to capture this feature without the need of specifying parameters that regulate the penetration of wind over time. In EleMod, various generation technologies (characterized by a wide range of investment and operating costs, diverse energy sources and operating regimes[20]) are combined to

[20]Mainly depending on their variable operating costs and operational flexibility, conventional power plants are operated under different regimes normally known a peaking, intermediate and base-load.

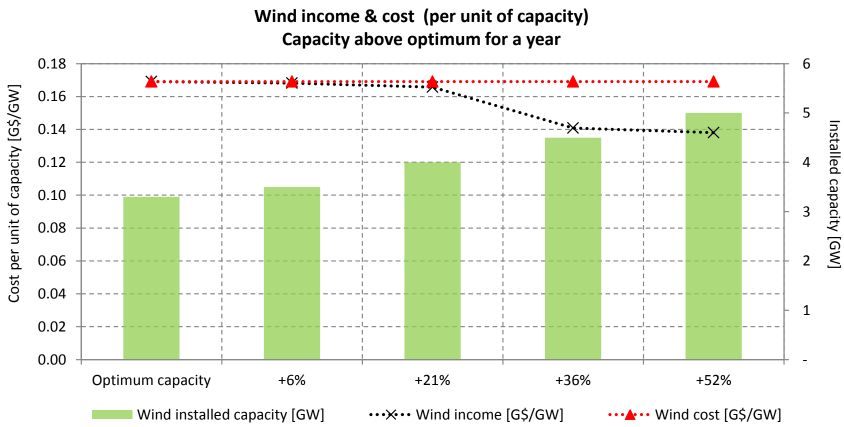
supply demand at different timescale generally based on economic efficiency and system reliability criteria. Thus, new investments in wind —or any other technology— are optimally done to the point where any extra profits from supplying electricity are zero (i.e. every year wind grows up to a level where revenues are attractive enough to cover their costs, where capital costs obviously include a reasonable rate of return).

Appendix E. Wind technology long-term equilibrium

The following numerical simulations demonstrate that, in equilibrium, there is an optimum amount of wind every year that completely recovers its costs via correctly designed market prices. If more wind were installed, then the technology would not recover costs because of a flattening effect on electricity prices and subsequent revenue drop in the short-term. On the contrary, if less wind were installed below the optimum level, then the technology would have a revenue stream larger than the costs giving wind owners an incentive to install more wind until eventually the optimum amount is reached.

Several simulation runs were performed around the optimum solution found for a particular year of the reference scenario (year 10 in the examples below). Then, the desired amount of wind capacity —either above or below the optimum level— was set while keeping energy and reserve requirements fixed. Figure E.18 displays the effects —lower income and lower electricity market prices— for the case of having more wind with respect to the optimal case for a particular year.

Figure E.19 displays the effects of having less wind with respect to the optimal case for a particular year, i.e. higher income for wind in the short term (as seen in the figures, there is no great variation on the electricity market prices).



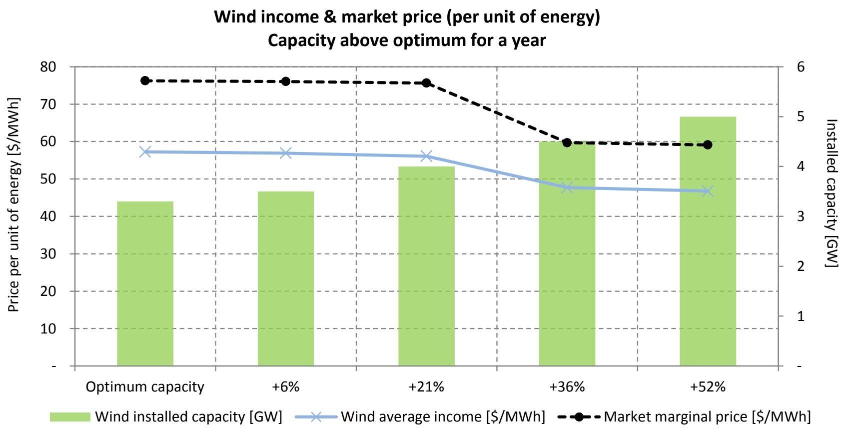


Figure E.18: Wind income and cost per unit of capacity (a) and market marginal prices vs. wind average income per unit of energy (b) if wind capacity *above* optimum.

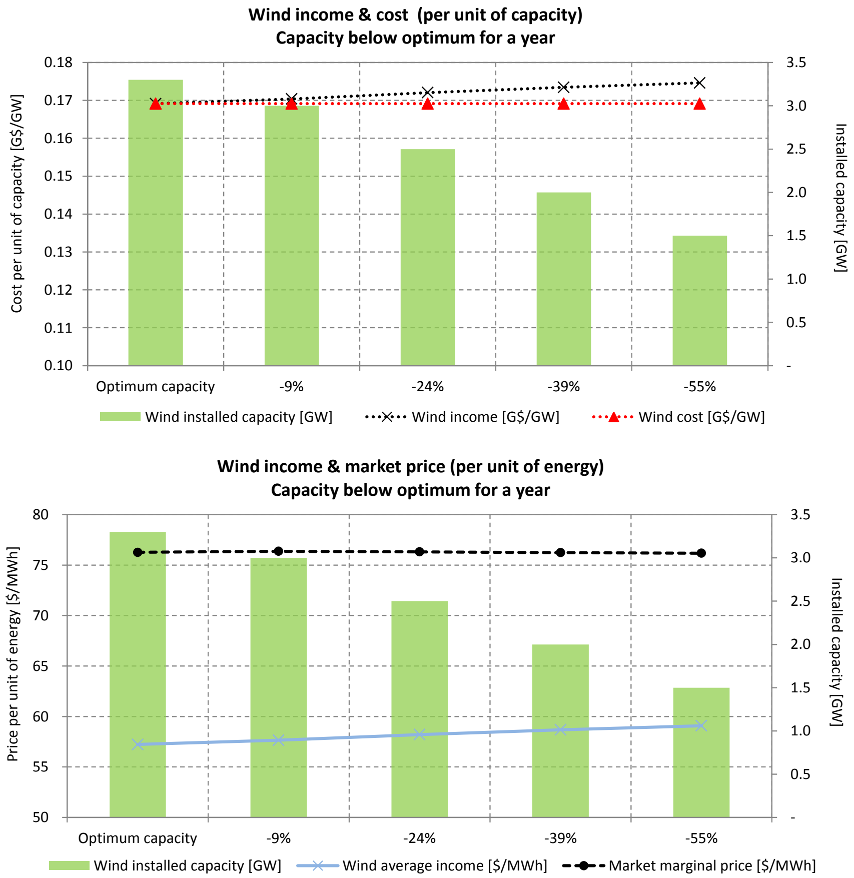


Figure E.19: Wind income and cost per unit of capacity (a) and market marginal prices vs. wind income per unit of energy (b) if wind capacity *below* optimum.