Modeling intermittent renewable electricity technologies in general equilibrium models*

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ABSTRACT

Economy-wide top-down (TD) equilibrium 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 a careful review of existing tools. This paper presents an overview of TD modeling approaches for incorporating renewable energy and describes in detail one approach, using the MIT USREP model, to identify critical parameters and assumptions underlying the general equilibrium formulation. We then quantitatively assess its performance regarding the ability to correctly estimate the participation of intermittent renewables in the electricity sector as predicted by a bottom-up electricity sector model, which is designed to analyze the expansion and operation of a system with a large penetration of wind and which is integrated within an economy-wide general equilibrium framework. We find that a properly specified TD approach to modeling intermittent renewable energy is capable of roughly replicating the results from the benchmark model. We argue, however, that the general equilibrium approach is highly sensitive to key parameters which are a priori typically unknown or at least highly uncertain. Our analysis suggests that traditional TD simulation tools have to be enhanced to avoid potentially misrepresenting the implications of future climate policies where presumably renewable energy could participate at large scale. Detailed power system models that capture system reliability and adequacy constraints are needed to properly assess the potential of renewable energy.

1. Introduction

Macro-economic "top-down" (TD) equilibrium 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 emission reduction potentials) and their social costs and benefits.[1] While these models are used to derive policy recommendations, the "current generation" of TD approaches seems to lack the required detail and model features to adequately represent intermittent renewable energy sources.[2] Intermittent wind and solar energy resources require detailed temporal and spatial analyses, as well as, the study of operational implications such as the need for additional reserve requirements, storage and transmission capacity. General

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[1] See, for example, the TD equilibrium models used in inter-model comparison activities such as the Stanford Energy Modeling Forum (e.g., Fawcett et al., 2014 and the work to expand the GTAP dataset for energy and climate policy analysis Nijkamp et al., 2005).

[2] Traditional modeling approaches, both in the domains of economy-wide 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. 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. 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.

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equilibrium models do not have this level of detail in their formulation. The substantial and rapid increase of renewable intermittent energy sources over the past two decades, and their expected significant role in future energy systems, represent a major challenge for the further advancement of simulation models that inform climate policy design.

The objective of this paper is two-fold. First, it presents an overview of TD modeling approaches for incorporating renewable energy and describes in detail one approach to identify critical parameters and assumptions underlying the general equilibrium formulation.

Second, by quantitatively comparing a TD approach against a benchmark model that adopts an explicitly structural engineering-type "bottom-up" (BU) methodology, our analysis offers insights into how important the pitfalls of the TD approach can be. To perform our computational experiments, we use a TD general equilibrium model, both as a stand-alone model and as the component of a proposed integrated modeling framework, to look at the evolution of the energy mix with increasing penetration of wind.

To this end, we first develop a detailed BU model of the electricity sector that has been specifically designed to analyze the capacity expansion and operation of a system with large penetration of wind (Tapia-Ahumada and Pérez-Arriaga, under preparation). We put emphasis on a sufficient temporal resolution — i.e., an hourly characterization — of both wind resources and electricity demand to better capture the impacts of intermittency on the system's generation mix and operation in the long term.[3] In a second step, we then fully integrate this BU model with an economy-wide general equilibrium framework to obtain a benchmark model against which we can evaluate the performance of a TD approach to modeling intermittent renewable energy.[4] The TD component of our integrated model is based on the MIT U.S. Regional Energy Policy (USREP) model, a recursive-dynamic, multi-sector, multi-region, numerical general equilibrium model designed to analyze climate and energy policy in the United States (Rausch et al. 2010, 2011).

Our analysis is germane to the literature on integrating TD and BU models for carbon policy assessment (see Hourcade et al. (2006) for an overview). Following the seminal methodological contribution of Boehringer and Rutherford (2009) on "hard-linking" TD and BU models, an important feature of our modeling approach is that the optimization of the electric sector — with modeling details to represent intermittent generation from wind — is fully consistent with the equilibrium response of the economy, including endogenously determined electricity demand and prices for fuels, goods and intermediate inputs to production. There are only a few studies that 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 approach, but their framework has considerably less detail with respect to modeling important features of renewable electricity generation. Rausch and Mowers (2014) link an economy-wide general equilibrium model to NREL's ReEDS (Regional Energy Deployment System) model (Short et al., 2011), a linear programming model that simulates the least-cost expansion of electricity generation capacity and transmission, with detailed treatment of renewable electric options. They do not, however, investigate the suitability and performance of alternative modeling approaches to intermittent renewables.[5]

On a more general level, the goal of the analysis is to examine the implications of different structural modeling choices within general equilibrium models with respect to representing intermittent renewables. Thus, it also relates to the literature on role of functional forms in CGE models, and the limitations of representing some production processes with CES functions (McKitrick, 1998). Given the widespread 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. While it should be clear that the results presented here are based on comparing a BU approach with one particular TD approach, we nevertheless believe that the present analysis contributes to understanding the usefulness and limitations of employing numerical simulation models for economic policy analysis of economy-energy systems with significant levels of energy production from highly intermittent renewable resources.

The paper is organized as follows. Section 2 provides a brief overview of modeling approaches to represent intermittent renewables in TD general equilibrium models, and describes the USREP model renewable formulation as an example. Section 3 provides a description of the BU model for the electricity sector and details the methodology adopted to integrate the TD and BU modeling approaches. Section 4 presents the results, both from the TD-only model and the integrated model, and compares the performance of the TD-only approach through a sensitivity analysis. 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, Labandeira et al. (2009)) — 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 in 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 are specifying whether or not electricity is a homogeneous good (i.e., electricity supplies generated from different technologies are perfect or imperfect substitutes) and how different generation technologies trade off against each other. This typically entails choosing a specific nesting structure for CES functions among 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. This includes, for example, approximating in a reduced manner back-up generation and other

[3] 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).

[4] Note that we do not claim that the integrated modeling approach which serves as a benchmark for the evaluation of the TD model truthfully portrays reality.

[5] Hybrid modeling work in analyzing other sectors of the economy has also been attempted, see for example Karplus et al., 2013.

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 the five main approaches that have been adopted so far:

- First, TD models like the IGEM models — an econometrically estimated GE model of the U.S. economy (Goettle et al., 2009) that is used by the U.S. Environmental Protection Agency (EPA) — do not provide any breakdown of electricity technologies.[6]
- Second, TD general equilibrium models like ADAGE (Ross, 2009) and older versions of the EPPA model (Paltsev et al., 2005) 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. (2005), 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 predetermined 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.
- Fourth, 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 outcome by restricting the solution space using the so-called CRESH (constant ratio elasticity of substitution homothetic production function) aggregate production function (Hanoch, 1971), 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 particularly relevant for intermittent renewables. Moreover, electricity is a homogeneous good from the consumer perspective but not from the supply side, which causes inconsistencies in the GE setting and potential problems with welfare accounting.
- Fifth, another category of TD models, for example, a more recent version of the MIT EPPA model (Paltsev et al., 2005) and the MIT USREP model (Rausch et al., 2011), is based on an approach put forward by Morris et al. (2010) who treat electricity as a homogeneous good and specifies "synthetic" electric generation technologies that combine intermittent renewable energy with back-up capacity in order to render intermittent renewable energy technologies fully dispatchable (and thus to make them comparable with dispatchable fossil-based technologies). We describe this approach in more detail in the next section.

[6] 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.

2.2. TD modeling of electricity generation from intermittent wind resources in the USREP model

Electricity generation is portrayed by the cost minimization problem[7] 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[8] (McFarland et al., 2004; Paltsev et al., 2005). This factor can be thought of as the costs of accumulating engineering knowledge and regulatory capacity to scale up new technologies. Following Paltsev et al. (2005) 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 their 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 back-up (*windgas*), and large-scale wind 100% biomass back-up (*windbio*). Both technologies constitute perfect substitutes for electricity from dispatchable sources (Rausch and Karplus, 2013; Rausch et al., 2010).

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 within the generation mix, and how inputs to production are combined to produce electricity in each of the technologies (see Fig. 1 for one possible choice, which is adopted in the EPPA and USREP models). The structure of the CES function is critical in determining model results, in particular the substitution of energy for other inputs to production, as described by Lecca et al. (2011).
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. As discussed by Zha and Ding (2014), elasticities of substitution are key parameters determining the participation of different inputs to production in the power sector.
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* 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 mathematically describes the modeling of these four features to represent intermittent wind energy.[9]

[7] General equilibrium is cast as a mixed complementarity problem (MCP) based on the microeconomic principles underlying 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 behaviors imply that zero-profit and market clearing conditions have complementary slackness with respect to production levels and market prices, respectively (Markusen and Rutherford, 2004).

[8] 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. (2005).

[9] 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).

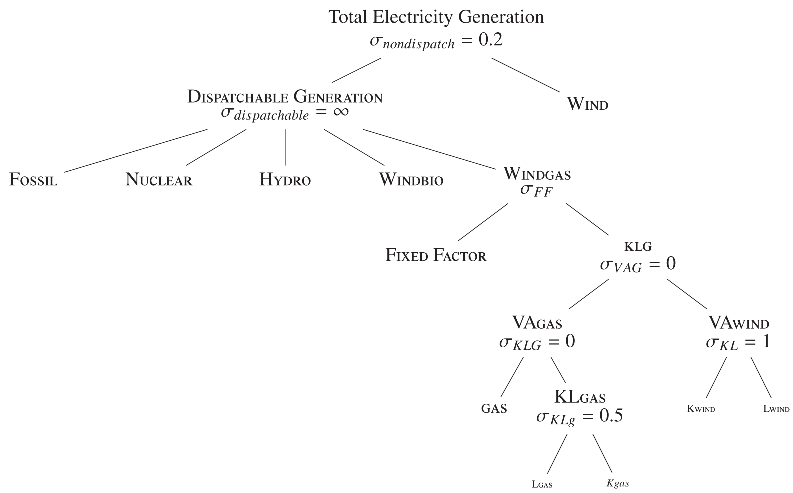

Fig. 1. Nesting structure for electricity generation. *Note*: The figure depicts only *windgas* technology in the lower levels. For fossil, nuclear and hydro see Lanz and Rausch (2011).

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 Fig. 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[10]:

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

where $\pi^{windgas}$ denotes the unit profit function of the *windgas* technology.[11] Assuming a nested CES structure for *windgas*, as shown in Fig. 1, $\pi^{windgas}$ can be derived from the dual cost minimization problem:

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

Wind is required to operate with 100% back-up capacity provided here by a gas turbine. The perfect complementarity between both technologies is reflected by a Leontief structure, i.e., $\sigma_{VAG} = 0$. The price of the capital–labor–gas composite, P^{KLG}, is given by:

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

where,

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

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

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

The equilibrium conditions for electricity generation from the other wind technologies (i.e., $ELE^{windgas}$, $ELE^{windbio}$ and $ELE^{windnoback-up}$) can be derived similarly, following the nesting structure for *windbio* and *wind* as shown in Figs. 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:

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

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. Eqs. (5)–(6) give the capital and labor market equilibrium conditions, respectively.

$$K = D^{K} + \overline{ELE}^{Fossil}\frac{\partial\pi^{Fossil}}{\partial P^{K}} + \overline{ELE}^{Hydro}\frac{\partial\pi^{Hydro}}{\partial P^{K}} + \overline{ELE}^{Nuclear}\frac{\partial\pi^{Nuclear}}{\partial P^{K}} + \overline{ELE}^{wind}\frac{\partial\pi^{wind}}{\partial P^{K}} \perp P^{K} \tag{5}$$

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

$$L = D^{L} + \overline{ELE}^{Fossil}\frac{\partial\pi^{Fossil}}{\partial P^{L}} + \overline{ELE}^{Hydro}\frac{\partial\pi^{Hydro}}{\partial P^{L}} + \overline{ELE}^{Nuclear}\frac{\partial\pi^{Nuclear}}{\partial P^{L}} + \overline{ELE}^{wind}\frac{\partial\pi^{wind}}{\partial P^{L}} \perp P^{L} \tag{6}$$

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

[11] 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, $ELE^{windgas}$.

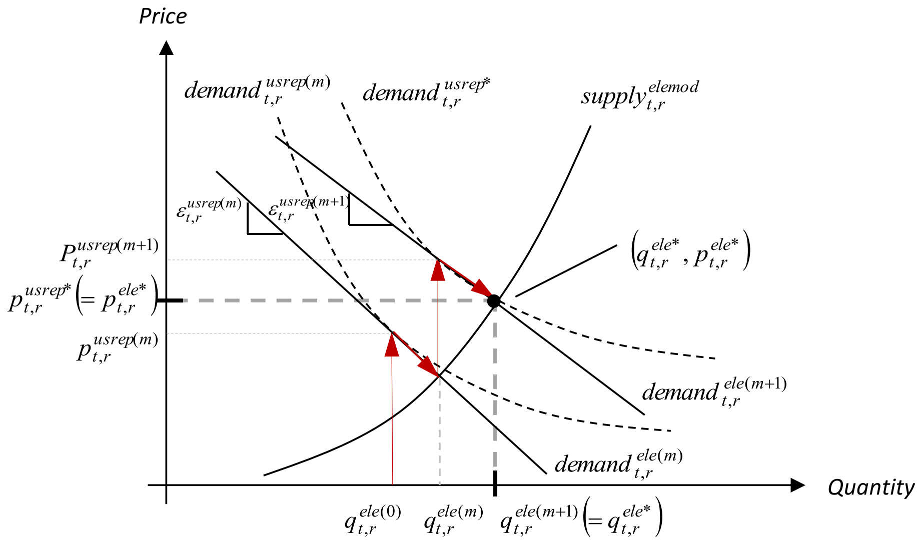

Fig. 2. Iterative methodology of the integrated model approach.

where L is the labor supply in the economy, D^L is the demand for labor from non-electricity sectors and $\frac{\partial \pi^{Fossil}}{\partial P^L}$, $\frac{\partial \pi^{Hydro}}{\partial P^L}$, $\frac{\partial \pi^{Nuclear}}{\partial P^L}$, and $\frac{\partial \pi^{wind}}{\partial P^L}$ 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[12] is given by Eq. (8).

$$S^{wind} = \overline{ELE}^{wind} \frac{\partial \pi^{wind}}{\partial P^{wind}} \perp P^{FF} \tag{7}$$

$$S^{gas} = D^{gas} + \overline{ELE}^{Fossil} \frac{\partial \pi^{Fossil}}{\partial P^{gas}} + \overline{ELE}^{windgas} \frac{\partial \pi^{windgas}}{\partial P^{gas}} \perp P^{gas} \tag{8}$$

where S^{wind} is the supply of the fixed factor resource for wind, $\overline{ELE}^{wind}$ is the benchmark production of wind, and $\frac{\partial \pi^{wind}}{\partial P^{wind}}$ 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 modeled as an imperfect substitute of dispatchable generation. The values adopted for elasticity of substitution $\sigma_{nondispatch}$ 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., $\sigma_{dispatchable} = \infty$ (see Fig. 1 above).

One key decision to control the penetration pattern of *windgas* and *windbio* technologies is the region-specific elasticities of substitution for the fixed resource factor, σ_{FF}, as shown in Eq. (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 potentials 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,[13] 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. 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 the 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 Eq. (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

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

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

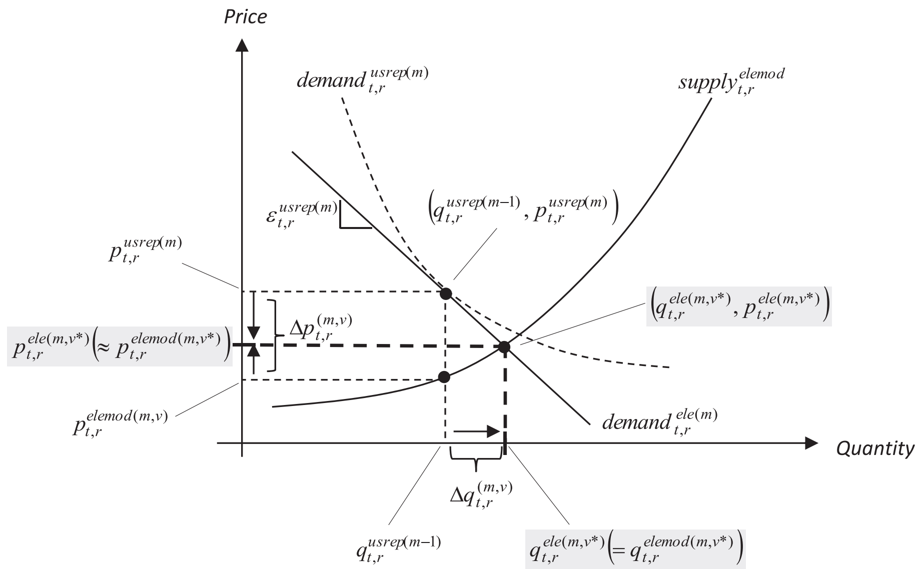

Fig. 3. Incorporation of demand response within the BU electricity model.

LCOEs for the different technologies, the mark-up parameter μ_n is estimated according to:

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

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

It should be noted that 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 problematic 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, determining the economics of wind and solar technologies. In the TD approach with back-up capacity, several assumptions are inaccurate in terms of 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 North American Electric Reliability Corporation (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 described 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 is not the only technology that demands backup; for example, inflexible nuclear plants also need flexible generation to follow demand or to provide fast operating reserves in 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. Thus, further research that provides new metrics to compare electricity technology costs considering system costs could prove helpful for top-down modelers (see for example Hirth et al. (2014)) or integrated approaches as the one put forward in this paper that explicitly models the electric sector technical constraints.

2.2.4. Resource supply and dynamics over time

The fixed factor controls the technology penetration pattern, once it becomes competitive. As shown in Eq. (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 Eq. (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 with a clearing condition as shown in Eq. (7).

In any given period, the resource S^{wind} is fixed and specified with a very small amount in the first period which we denote by $inish^{wind}$. 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:

$$S_{t=2}^{wind} = S_{t=1}^{wind} + inish^{wind}\theta^{FF}\mu_{windgas}ELE_t^{windgas} \tag{11}$$

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

where S_t^{wind} is the wind fixed factor supply in period t, $inish^{wind}$ is the parameter that initializes the fixed endowment, θ^{FF} is the benchmark value share of the fixed factor, $\mu_{windgas}$ is the mark-up parameter, $\overline{P}^{ELE}$ is the benchmark price for electricity, $ELE_t^{windgas}$ is the production level of windgas technology in period t; and α, β and ς are the parameters that allow a smooth penetration of the technology.[14]

[14] 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.

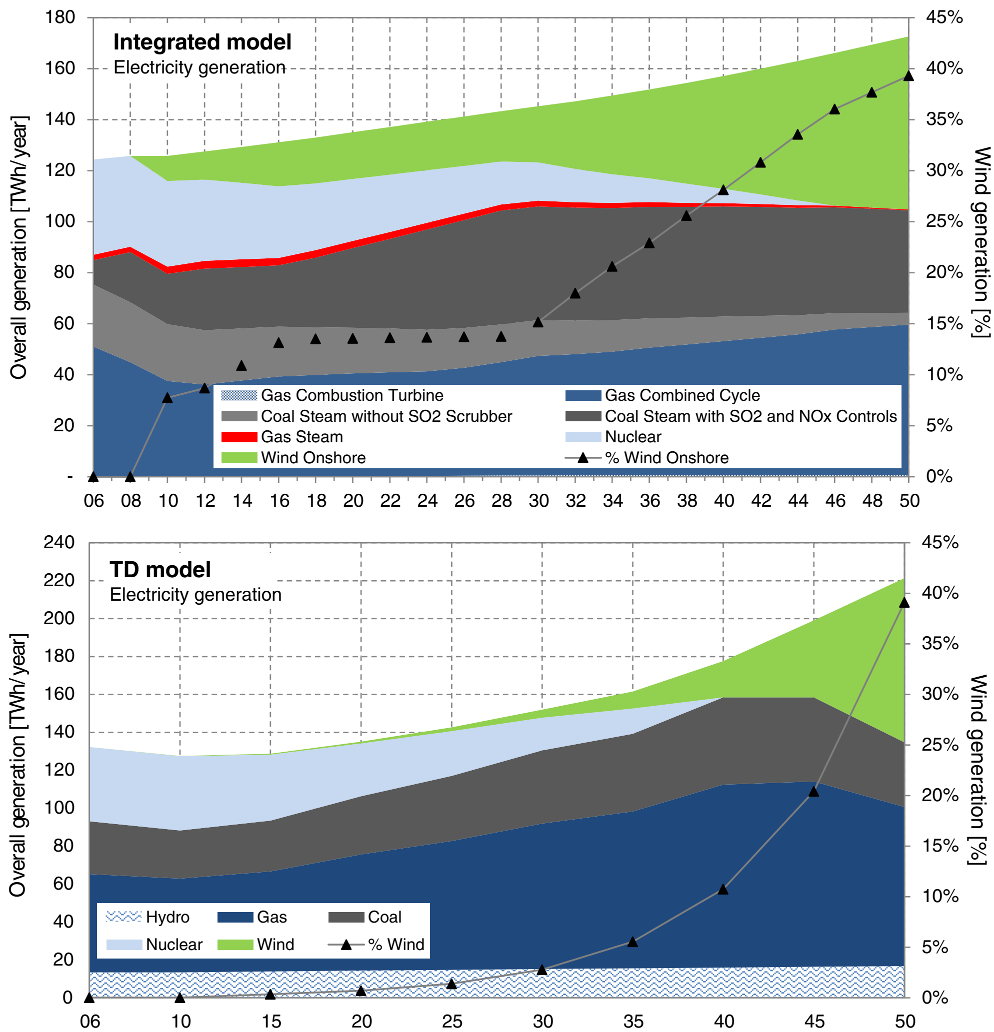

Fig. 4. Electricity generation per technology from years 2006 to 2050 for New England region. Results from integrated model (a) and from TD model with mark-up = 0.885 and fixed factor = 0.0002 (b).

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 "hard-links" two sub-models coupled via an iterative algorithm, similar to the framework implemented by Rausch and Mowers (2014) 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 (Meseguer et al., 1995; Pérez-Arriaga and Meseguer, 1997), a large-scale generation expansion power system tool that has been extensively used to analyze the Spanish power system, in particular, to understand

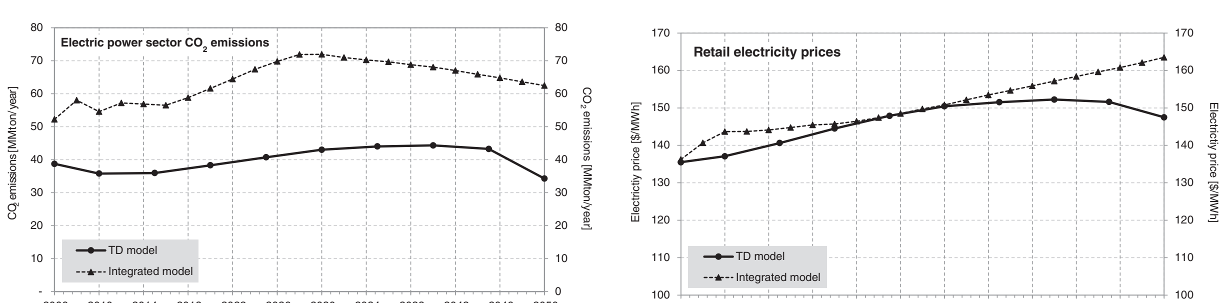

Fig. 5. Electric power sector CO_2 emissions (a) and retail electricity price (b) from years 2006 to 2050 for New England region. Results for integrated model (black triangles) against TD approach with mark-up = 0.885 and fixed factor = 0.0002 (black circles).

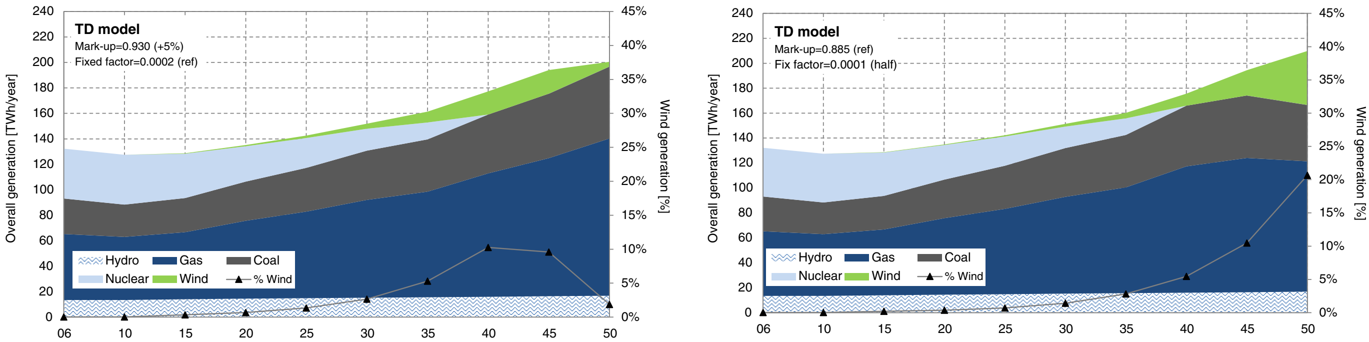

Fig. 6. Electricity generation per technology from years 2006 to 2050 for New England region. Results from TD model with mark-up = 0.930 (+5%) (a) and fixed factor = 0.0001 (half) (b).

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 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 in the system. The model preserves the hourly variability of both wind resources and electricity demand for different U.S. regions. While our model does not incorporate a probabilistic analysis — which is an area of further research given the computational times required to link models of such long time scales and geographic coverage — we believe that the hourly profiles and technical operational details provide an improved portrayal of renewable energy characterization. Details of EleMod's mathematical formulation are provided in Appendix B, and a comprehensive description of the model can be found in Tapia-Ahumada and Pérez-Arriaga (under preparation).

Both TD and BU models adopt a sequential optimization 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 the TD model, a set of dynamic equations describe the evolution of capital and energy resources over time, whereas in the BU model 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 TD and BU models

The two sub-models are coupled via an iterative algorithm that looks for a consistent solution in both models. To integrate the BU production model into the TD model, 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 a set of modified market clearing conditions, the values determined by the BU model are used to parameterize the TD model according to the algebraic formulation already outlined by Lanz and Rausch (2011). This section focuses on the implementation of this iterative procedure and on the incorporation of demand response into the BU model by means of an approach that maintains its linear and temporal characteristics while looking for the equilibrium condition.

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 model, over all regions and technologies, are equivalent to the aggregate representation of the electricity sector in the economic Social Accounting Matrix (SAM) data that underlies the TD model. At benchmark $m = 0$ and based on historical prices $p_{r,n}^{\mathrm{fuel}(0)}$ for each fuel n, electricity demands $q_r^{\mathrm{ele}(0)}$ and variable O&M prices $p_r^{\mathrm{vom}(0)}$, the BU model computes the optimal expansion and operation of the sector for every region r. It determines, among other results, the annual average load-weighted price $p_{t,r}^{\mathrm{elemod}(0)}$ from the hourly wholesale electricity prices and the aggregated generation output $q_{t,r}^{\mathrm{elemod}(0)}$, which by construction, is equal to $q_{t,r}^{\mathrm{ele}(0)}$ in the benchmark. Given the simulated data from the BU model, we adjust the SAM data of the TD model to generate a micro-consistent benchmark for the integrated model that reconciles the macro-economic and electricity-sector data according to the approach described in Rausch and Mowers (2014). 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 Fig. 2). In iteration $m \geq 0$, the TD model simulates the rest of the economy based on regional information of the electricity sector obtained from the last known BU solve (i.e., benchmark $m = 0$), including the aggregated generation supply $q_{t,r}^{\mathrm{ele}(0)}$, annual CO_2 emissions $em_{t,r}^{\mathrm{elemod}(0)}$, capital expenditures[15] in generating technologies $k_{t,r}^{\mathrm{elemod}(0)}$, fuel expenditures $s_{t,r,n}^{\mathrm{elemod}(0)}$, and variable O&M expenditures shared out across labor, materials, services and other components. Based on this information, the TD model is solved, which yields a set of solutions that include the values for elasticity $\varepsilon_{t,r}^{\mathrm{usrep}(m)}$, demand $q_{t,r}^{\mathrm{usrep}(m)}$ and price $p_{t,r}^{\mathrm{usrep}(m)}$, in addition to fuel price indexes $pi_{t,r,n}^{\mathrm{fuel}(m)}$ and variable O&M price indexes $pi_{t,r}^{\mathrm{vom}(m)}$.

The solution derived from the TD model is now used to solve the BU model 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 Eqs. (13)–(14).

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

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

As seen in Fig. 2, the electricity demand from the TD model is non-linear. In order to incorporate demand response within the supply cost model, we approximate the demand curve with a linear function locally calibrated around the TD solution according to:

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

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

[15] Sunk costs are taken into account both by the differentiation of malleable and non-malleable capital in the TD model and by tracking initial capacity and depreciation of technologies through time in the BU model. The BU model will install capacity only if it is economically viable. These costs will then be considered in the capital expenses passed to the TD model.

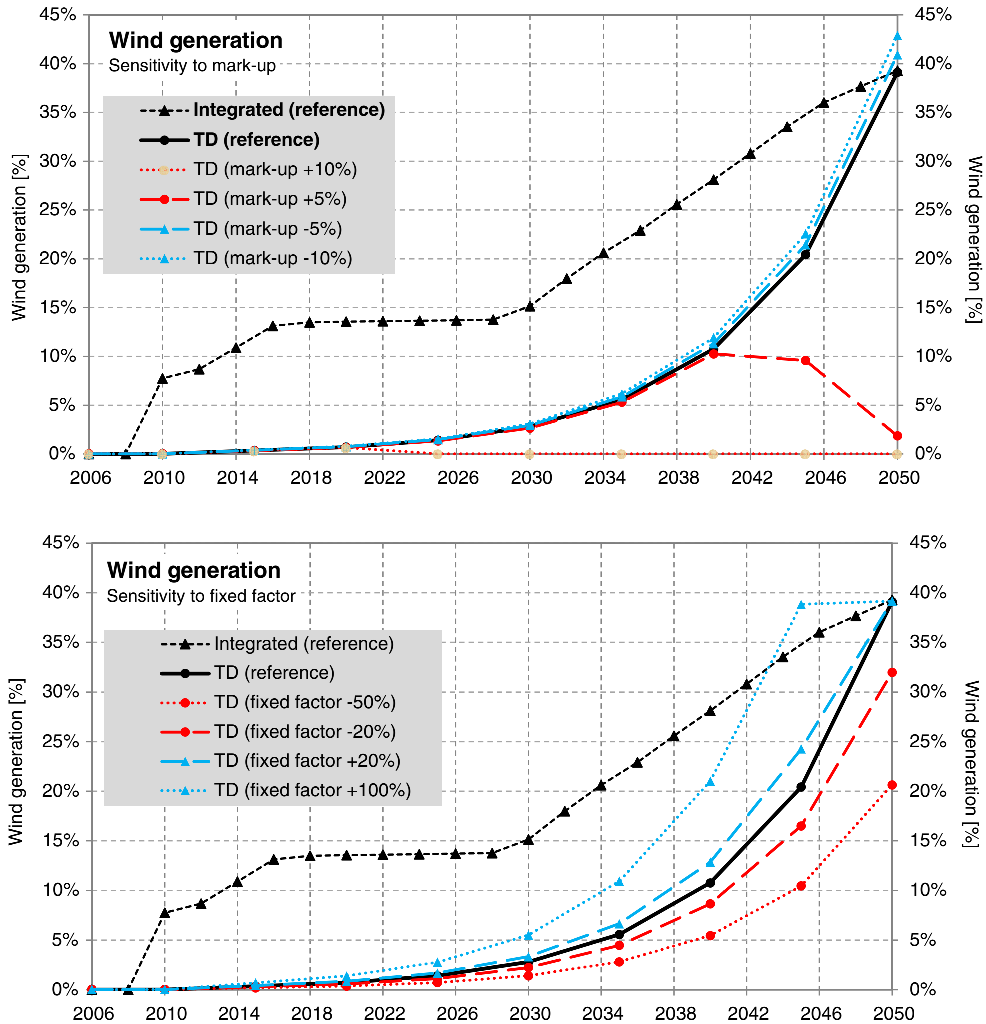

Fig. 7. Wind generation as % of total generation from years 2006 to 2050. Sensitivity to mark-up factor (a) and sensitivity to fixed factor (b). Results from TD approach compared against integrated model.

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

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, 2014). Since the BU formulation works with an objective function that minimizes total investment and production costs for a given level of demand — including the possibility of non-served demand at a prescribed high variable cost per kWh — in each hour, an alternative approach is required. As Fig. 3 shows, an additional iterative method is implemented only within the BU model.

Let v denote a sub-iteration within iteration m:

1. For *sub-iteration* v, the BU model is solved for the known values of annual electricity demand $q_{t,r}^{usrep(m)}$ and price $p_{t,r}^{usrep(m)}$ passed by the TD solution. Electricity prices $p_{t,r}^{elemod(m,v)}$ are then estimated for each one of the regions and then compared to $p_{t,r}^{usrep(m)}$. The difference $\Delta p_{t,r}^{(m,v)} = p_{t,r}^{usrep(m)} - p_{t,r}^{elemod(m,v)}$ is calculated. If $|\Delta p_{t,r}^{(m,v)}|$ is small, then the found BU solution is deemed optimal. Otherwise, the electricity demand $q_{t,r}^{usrep(m)}$ is increased by an amount $\Delta q_{t,r}^{(m,v)}$ if $\Delta p_{t,r}^{(m,v)} > 0$ (or decreased if $\Delta p_{t,r}^{(m,v)} < 0$).
2. For *sub-iteration* $v+1$, the BU model is run now taking the modified demand $q_{t,r}^{ele(m,v+1)} = q_{t,r}^{usrep(m)} + \Delta q_{t,r}^{(m,v)}$. New electricity prices $p_{t,r}^{elemod(m,v+1)}$ are calculated. Using Eq. (15), it is possible to approximate the TD model demand curve to a linear demand function and obtain $q_{t,r}^{elemod(m,v+1)}$ and price $p_{t,r}^{ele(m,v+1)}$ along the line. Then, the difference $\Delta p_{t,r}^{(m,v+1)} = p_{t,r}^{ele(m,v+1)} - p_{t,r}^{elemod(m,v+1)}$ 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 $|\Delta p_{t,r}^{(m,v^*)}|$ is satisfactorily small in iteration v^*, indicating that the price of the approximate demand function is close enough to the price calculated by the supply function. Finally, iteration m of the TD–BU algorithm is complete. The optimum solutions[16] $q_{t,r}^{ele(m,v^*)}$, $em_{t,r}^{ele(m,v^*)}$, $k_{t,r}^{ele(m,v^*)}$ and $s_{t,r,n}^{ele(m,v^*)}$ derived from the last BU run are then passed to the TD model to carry out the next iteration $m+1$.

3.2. Short-term dynamics and electricity pricing

Since the TD model is defined on an annual basis and the BU model is characterized by hourly loads and generation profiles, reconciling the time scale is required. The annual TD electricity demand $q_{t,r}^{usrep(m)}$ is

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

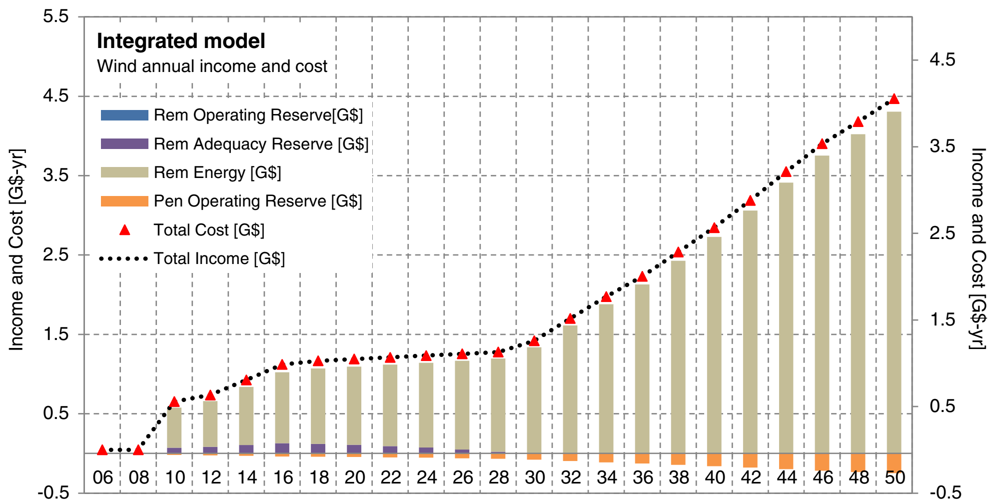

Fig. 8. Total annual income and cost for wind — disaggregated by component and over time (years 2006 to 2050).

scaled across each hour of the year according to hourly factors obtained from regional historical demands provided by NREL. The optimization in the BU model is thus done for the sum of each hour, per region, in order to capture geographic and temporal characteristics. Results are then aggregated and passed back to the TD model.

In addition, electricity prices constitute a major linkage between the TD model and the power sector model. By minimizing total electricity production costs, the BU model 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 long term guarantee of supply 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, under preparation).

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

$$P^{\mathrm{ele\,mod}(m)}_{t,r} = \frac{1}{\sum_h d_{t,h,r}} \left(\sum_h (\rho_{t,h,r} d_{t,h,r}) + \sum_{h \in j} \left(\sigma^{UP}_{t,j,r} OR^{DW}_{t,j,r} \right) + (\tau_{t,r} MR_{t,r}) \right) \tag{16}$$

where the hourly regional demand is given by $d_{\mathrm{t,h,r}}$, the level of daily upward and downward operating reserves is given by $OR^{UP}_{t,j,r}$ and $OR^{DW}_{t,j,r}$ respectively, and the long-term guarantee of supply is given by $MR_{t,r}$ 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 the TD model $p^{\mathrm{usrep}(m)}_{t,r}$ at retail level and the calculated electricity price $p^{\mathrm{elemod}(m)}_{\mathrm{t,r}}$ at wholesale level, a regional distribution mark-up is estimated based on the difference between the TD and BU prices. Following the approach implemented by Rausch and Mowers (2014), these regional mark-ups 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 the BU model — in order to get the complete retail electricity price.[17]

4. Comparison of modeling approaches and sensitivity analysis

This section explores the evolution of an electricity system over time using both the integrated benchmark model and the TD-only approach. The relative performance of each modeling approach to intermittent wind energy is assessed by numerical simulations. We then assess the robustness of the TD-only approach (vis-à-vis the benchmark model) by means of a parametric sensitivity analysis with respect to key parameters used to characterize 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[18] ($203/kW-year from 2006 to 2008, and $170/kW-year from 2010 to 2050).[19] Second, a scenario is constructed in the TD model that approximately replicates the outcomes of the integrated model. In both cases, neither a renewable energy mandate nor a 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. Results from the integrated "benchmark" model

The evolution of the energy mix over time is displayed in Fig. 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 C). Clearly, the penetration of wind critically depends on the cost assumptions, where the relatively high costs during the first years

[17] Convergence between the two sub-models is achieved after approximately eight iterations. Boehringer and Rutherford (2009) demonstrate, for the solution algorithm applied here, that a Marshallian demand approximation in the energy sector model provides a good local representation of the general equilibrium demand. In the context of our specific application, rapid convergence is also observed due to the fact that the value share of the electricity sector is relatively small (about 4%) of the economy-wide output.

[18] 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 BU model are based on values used by NREL's ReEDS model as of year 2011.

[19] 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.

represent a barrier for its deployment. Once technology costs decrease by year 2010, it is seen a big leap in wind generation until 2016, followed by a smooth 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 $MMTCO_2$ in 2050 or, equivalently, 20% above the emission level of year 2006 (see Fig. 5a). After 2028, the deployment of wind helps to stabilize emissions coming from the growing electricity production of fossil-fueled conventional technologies, mostly gas and coal-fired power plants.

The electricity prices for the region experience a 20% or $27/MWh increase over a period of 44 years (see Fig. 5b), as a consequence of greater electricity 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 coming from coal and natural gas by the end of the period.[20]

4.2. 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 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 Fig. 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 mark-up $\mu < 1$, because its penetration is controlled by the fixed factor input requirement that 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. 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 (see Fig. 5a). Retail electricity prices in both cases are quite close until year 2030, after which prices deflate as wind becomes more important within the energy mix (see Fig. 5b).

Summing up, we conclude that if a well-informed parameterization is used in the TD-only approach based on prior results from the integrated model, the TD framework 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.

4.3. Sensitivity analysis of the TD-only approach

Section 2 has identified 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 that vary two of these critical parameters. Here, we focus on the mark-up parameter and the initial fixed factor endowment.[21]

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 (coal) in the benchmark data. 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 and will represent less than 2% as opposed to 39% of total electricity generation in the baseline case (see Fig. 6a). Second, the initial fixed factor endowment *inish* in Eq. (11) 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 the TD approach will be significantly slower, reaching about 20% (instead of 39%) of the generation mix by 2050 (see Fig. 6b).

Further analysis illustrating the range of outcomes due to modest variations in either one of the parameters is shown in Fig. 7. If the mark-up factor μ_n fluctuates between 0.97 and 0.78, the share of wind varies between 0% and 43% in year 2050. If the fixed factor moves between 0.0001 and 0.0004, then the participation of wind fluctuates between 21% and 39%. In both cases, not only the final amount of wind changes, but also its penetration pattern over time. Fossil fuel generation also shows diverse outcomes as a direct consequence of the different projections of wind.[22] In addition, results display 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 the region range between −6% and +60% with respect to the reference value.[23]

These analyses show that the penetration of not only wind but also fossil-based generation 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 models — that can reproduce correctly the penetration pattern of intermittent renewables and the overall electricity generation mix.

4.4. Optimal equilibrium level of wind

Why does the TD approach potentially differ so much from the integrated model? One reason is as follows. From the simulation results, it is possible to observe that once wind is competitive, its penetration attained a natural limit and the technology did not dominate the market over time (see Fig. 4a). In a centralized planning and operation BU model, 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 when a combination of wind with other conventional technologies is a more cost-effective alternative than a combination without it. Results from the integrated

[20] Tapia-Ahumada et al. (2014) show the complete integrated model results for the electricity sector in New England.

[21] 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, σ_n^{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 therefore do not consider these parameters in our sensitivity analysis.

[22] Although the final mix of gas technologies ranges from 35% up to 63% in year 2050, we note that this variation is not because of the sensitivity of gas technologies to certain parameters used in their TD representation. This is something we did not explore in this paper.

[23] See Appendix D for results of CO_2 emissions and electricity prices.

model (see Fig. 8) show that — since some new capacity is added every year — wind capacity is always adapted in the sense that it fully recovers the costs (red triangles) through the income (dotted black line) it obtains for providing energy and reserves. In addition to the remuneration for energy (light brown), wind is also remunerated for its contribution to the system's capacity adequacy (purple), and it is 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, with the subsequent revenue drop in the short term.[24] 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.[25]

The TD approach when calibrated using information of the integrated model can roughly approximate its solution. However, our analysis suggests that — due to its highly aggregated structure — the TD-only approach cannot capture these relevant features of wind generation.

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 a careful 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 for future energy systems.

To this end, we have developed an integrated economy-electricity framework that incorporates a capacity planning and economic operation model of the power sector within an economy-wide general equilibrium framework. This enabled us to create a "benchmark" model that has been used to scrutinize the performance of a TD approach to modeling intermittent renewables. We have assessed the performance of the TD approach by (i) focusing on whether or not the model can reproduce a similar penetration of wind as predicted by the integrated model once it is competitive and (ii) 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 simulating the evolution of the electricity sector with a strong presence of wind as it would be predicted by an integrated modeling approach. If adequate information is available, which 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 without the assistance of detailed BU 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 a set of identified parameters. Using simulation-based analysis, we have shown that very small variations in these parameters — on the order of magnitude that TD modelers would usually consider to be negligible or "non-identifiable" — are sufficient to give rise to largely dissimilar 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 a 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 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 even when competitive. 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 framework showed a more realistic behavior of the electricity sector with high penetration of wind, where a mix of technologies is needed to meet demand.

As renewables become crucial for reaching a low-carbon economy, they add new complexities into 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 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 models (e.g., economy-energy computable general equilibrium) can be estimated and further refined to account for the adaptation of the electric power sector to high penetration of intermittent renewable energy sources.

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 TD model.

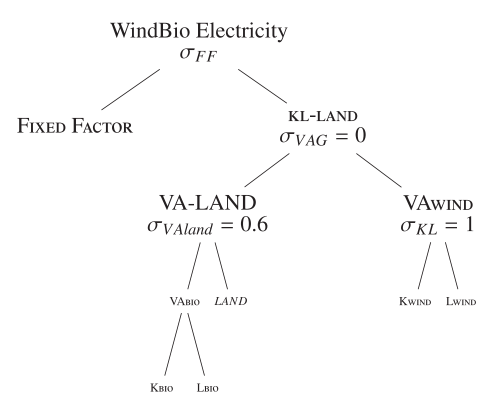

Fig. A.9. TD model nesting structure for *windbio* generation.

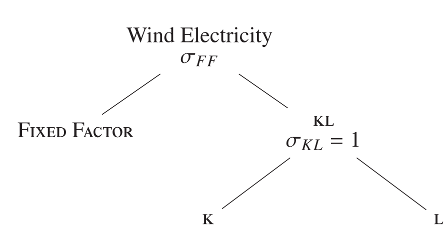

Fig. A.10. TD model nesting structure for *wind* generation.

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[24] 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.

[25] Refer to Tapia-Ahumada et al. (2014) for the methodology used for wind income calculations and results from numerical simulations.

Table A.1
Variables in the equilibrium conditions related to TD renewable electricity (*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 (capital–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 resource endowments in the economy

Table A.3
Inputs to production shares used in wind technologies in TD model (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: TD model input data based on Paltsev et al. (2005).

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

	Units	Pulverized coal	Wind	Wind plus biomass back-up	Wind plus NGCC back-up
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 TD model 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
Southeast	1.2	3.3	1.6
Northeast	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: TD 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. BU model mathematical formulation

The notation of the mathematical formulation is introduced in the tables below.

Table B.6
Indexes used in BU model.

Symbol	Name
r	Region
t	Year
j	Day
h	Hour
n	Thermal-based generation technology
c	Wind class technology

Table B.7
Inputs required in BU model.

Symbol	Name
$c_{r,n}^{fix}$	Annualized fixed cost for technology n, in region r
$cw_{r,c}^{fix}$	Annualized fixed cost for wind class c, in region r
$c_{r,n}^{su}$	Start-up cost for technology n, in region r
$p_{r,n}^{fuel}$	Fuel price for technology n, in region r
$hr_{r,n}$	Heat rate for technology n, in region r
$c_{r,n}^{vom}$	Variable operating and maintenance cost for technology n, in region r
p_r^{CO2}	Price for CO_2 emissions in region r
$ef_{r,n}^{CO2}$	CO_2 emission factor for technology n, in region r
c^{nse}	Penalization for non-served energy
$d_{t,h,r}$	Demand for year t, hour h, in region r
$k_{r,n}^0$	Installed capacity of existing thermal-based conventional generators per technology n, in region r
$kw_{r,c}^0$	Installed capacity of existing wind per class c, in region r
$rw_{r,c}$	Wind resource in region r, per class c
$\omega_{r,c,h}$	Wind generation profile in region r, for class c, hour h
lt_n	Economic lifetime of thermal-based conventional technology n
ltw_c	Economic lifetime of wind technology per class c
$f_{r,n}^{forced}$	Forced outage rate for conventional technology n, in region r
$f_{r,c}^{firm}$	Firm capacity of wind technology class c, in region r
$m_r^{reserve}$	Capacity margin reserves for long-term reliability in region r
$l_{r,n}^{min}$	Minimum load for conventional generators in region r, per technology n
$Cap_{t,r}^{CO2}$	CO_2 emissions limit in region r, for year t

Table B.8
Decision variables of BU model.

Symbol	Name
$vK_{t,r,n}$	Installed capacity in year t, per region r and conventional technology n
$vKw_{t,r,c}$	Installed wind capacity in year t, per region r and wind class c
$vG_{t,h,r,n}$	Generated power in year t, per hour h, per region r and conventional technology n
$vGw_{t,h,r,c}$	Generated wind power in year t, per hour h, per region r and wind class c
$vCP_{t,j,r,n}$	Connected power in year t, per day j, per region r and conventional technology n
$vSU_{t,j,r,n}$	Connected power started up from day $(j-1)$ to day j
$vSD_{t,j,r,n}$	Connected power shut down from day $(j-1)$ to day j
$vNSE_{t,h,r}$	Non-served energy in year t, per hour h, per region r

Table B.9
Information used in sequential optimization.

Symbol	Name
$\hat{K}_{z,r,n}$	Installed capacity in previous years z with $(z < t)$, in region r and per conventional technology n. The technology is retired from the system when it reaches its economic lifetime, i.e., $\sum_{z<t} l > lt_n$
$\hat{K}w_{z,r,c}$	Installed capacity in previous years z with $(z < t)$, in region r and per wind class technology c. Wind technology is retired from the system when it reaches its economic lifetime, i.e., $\sum_{z<t} l > ltw_c$

B.1. Objective function

The model minimizes the total annual costs of producing electricity in a region, considering annualized investment costs for conventional and wind technologies, fuel operational costs, start-up costs, and costs related to connected power of conventional technologies. In addition, a reliability criterion (non-served energy cost) and a penalization for any energy surplus have been included in the formulation. A carbon tax is built in if a CO_2 emission policy case is put in place. Decision variables include generation investments and operational decisions, such as daily connected power and hourly production.

$$\begin{aligned}\mathrm{Min}\,TC(r) = &\ \sum_{t,n} vK_{t,r,n}c^{fix}_{r,n} + \sum_{t,c} vKw_{t,r,c}cw^{fix}_{r,c}\Bigg) \\ &+\left(\sum_{t,h,n} vG_{t,h,r,n}\left(p^{fuel}_{r,n}hr_{r,n} + c^{vom}_{r,n} + p^{CO2}_{r}ef^{CO2}_{r,n}hr_{r,n}\right)\right) \\ &+\left(\sum_{t,j,h\in j,n}\left(vCP_{t,j,r,n}-vG_{t,h,r,n}\right)\right) + \left(\sum_{t,j,n} vSU_{t,j,r,n}c^{su}_{r,n}\right) \\ &+\left(\sum_{t,h} vNSE_{t,h,r}c^{nse}\right)\end{aligned} \tag{B.1}$$

B.2. Constraints

a. Balance of generation and demand:

$$\sum_{n} vG_{t,h,r,n} + \sum_{c} vGw_{t,h,r,c} + vNSE_{t,h,r} = d_{t,h,r} \quad \forall t,h,r \tag{B.2}$$

b. Upward[26] and downward reserve margins:

$$\begin{aligned}&\sum_{n}\left(vCP_{t,j,r,n}-vG_{t,h,r,n}\right) \geq 0.5 + 0.01d_{t,h,r} \\ &+0.20\left(\sum_{c}\hat{K}w^{cumulative}_{t,r,c}\omega_{r,c,h*}\right)\forall t,r,j,\in j\end{aligned} \tag{B.3}$$

$$\begin{aligned}&\sum_{n}\left(vG_{t,h,r,n}-vGP_{t,j,r,n}l^{min}_{r,n}\right) + \sum_{c} vGw_{t,h,r,c} \geq 0.01d_{t,h,r} \\ &+0.20\left(\hat{K}w^{cumulative}_{t,r,c}\omega_{r,c,h*}\right)\forall t,r,j,h\in j\end{aligned} \tag{B.4}$$

with,

$$h^{*} = \arg\max_{h\in j}\ \omega(r, class3, h) \tag{B.5}$$

$$\hat{K}w^{cumulative}_{t,r,c} = kw^{0}_{r,c}\ \ 1-\sum_{z<t}\frac{1}{ltw_c}\Bigg) + \sum_{z<t}\hat{K}w_{z,r,c} + vKw_{t,r,c} \tag{B.6}$$

$$vCP_{t,j,r,n} \leq \left(k^{0}_{r,n}\ \ 1-\sum_{z<t}\frac{1}{lt_n}\right) + \sum_{z<t}\hat{K}_{z,r,n} + vK_{t,r,n}\Bigg)\left(1-f^{forced}_{r,n}\right) \tag{B.7}$$

where $vCP_{t,j,r,n}$ is the available connected power defined as the capacity that needs to be online to respond to any system's security constraint (i.e., operating reserves).

c. Restrictions for wind capacity and energy production:

$$\hat{K}w^{cumulative}_{t,r,c} \leq rw_{r,c} \quad \forall t,r,c \tag{B.8}$$

$$vGw_{t,h,r,c} \leq \hat{K}w^{cumulative}_{t,r,c}\omega_{r,c,h} \quad \forall t,h,r,c \tag{B.9}$$

d. Long-term reliability requirement on installed capacity:

$$\begin{aligned}&\sum_{n}\left(k^{0}_{r,n}\ \ 1-\sum_{z<t}\frac{1}{lt_n}\right) + \sum_{z<t}\hat{K}_{z,r,n} + vK_{t,r,n}\Bigg)\left(1-f^{forced}_{r,n}\right) \\ &\sum_{c}\left(kw^{0}_{r,c}\left(1-\sum_{z<t}\frac{1}{ltw_c}\right) + \sum_{z<t}\hat{K}w_{z,r,c} + vKw_{t,r,c}\right)f^{firm}_{r,c} \\ &\geq \left(1+m^{reserve}_{r}\right)\left(\frac{1}{100}\sum_{h\in 100\ \text{peak hours}} d_{t,h,r}\right) \quad \forall t,r\end{aligned} \tag{B.10}$$

e. Start-up and shut-down constraints:

$$vCP_{t,j,r,n} = vCP_{t,j-1,r,n} + vSU_{t,j,r,n} - vSD_{t,j,r,n} \quad \forall t,j,r,n \tag{B.11}$$

f. Maximum and minimum generation constraints:

$$vG_{t,h,r,n} \leq vCP_{t,j,r,n} \quad \forall t,j,r,n,h\in j \tag{B.12}$$

$$vG_{t,h,r,n} \geq vCP_{t,j,r,n}\ l^{min}_{r,n} \quad \forall t,j,r,n,h\in j \tag{B.13}$$

g. Other constraints:

$$\sum_{h,n} vG_{t,h,r,n}ef^{CO2}_{r,n}hr_{r,n} \leq Cap^{CO2}_{t,r} \quad \forall t,r \tag{B.14}$$

Appendix C. Electricity sector results of integrated TD–BU model

C.1. Wind energy and capacity deployment

Fig. C.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 (see Fig. C.11a), and from 8% to 39% in terms of total electricity generation (see Fig. C.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 as 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 Fig. C.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 (see Fig. C.11b). It can be seen that the deployment of wind after 2028 helps to stabilize emissions coming from the growing electricity production of fossil-fueled 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 (see Figs. C.11a and C.12a), it can be seen that, as wind increases in capacity, gas technologies experience 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

[26] This work used 1% of the electricity demand, a 500 MW unit, and 20% wind forecast error.

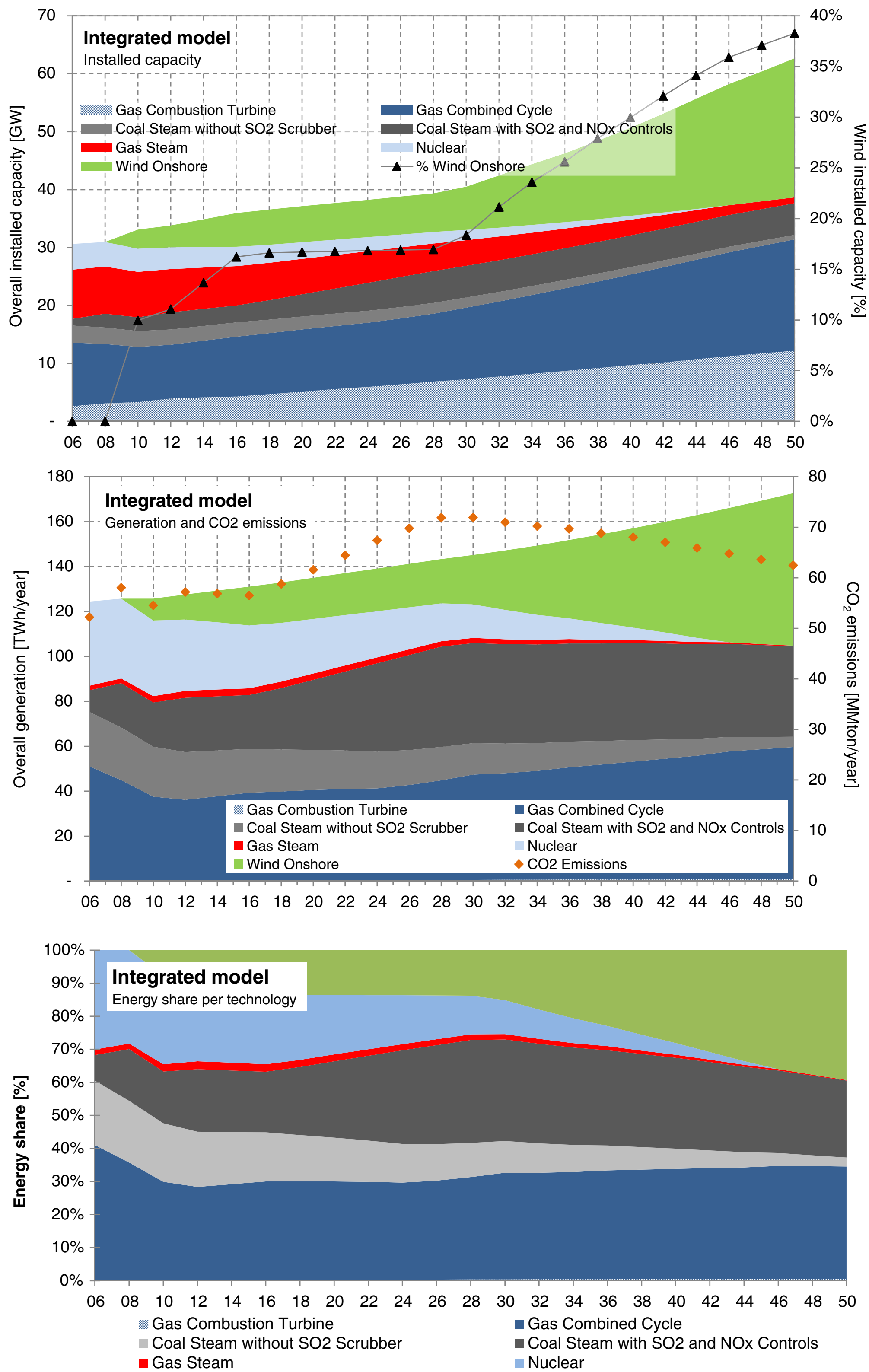

Fig. C.11. Cumulative installed capacity and % of wind over total installed capacity (a), electricity generation and regional CO_2 emissions (b), and electricity portfolio share per technology (c) from years 2006 to 2050.

guarantee of supply seems to become quite relevant under the presence of large amounts of wind. As Fig. C.12b displays, open cycle gas combustion turbines are mostly used for back-up 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.

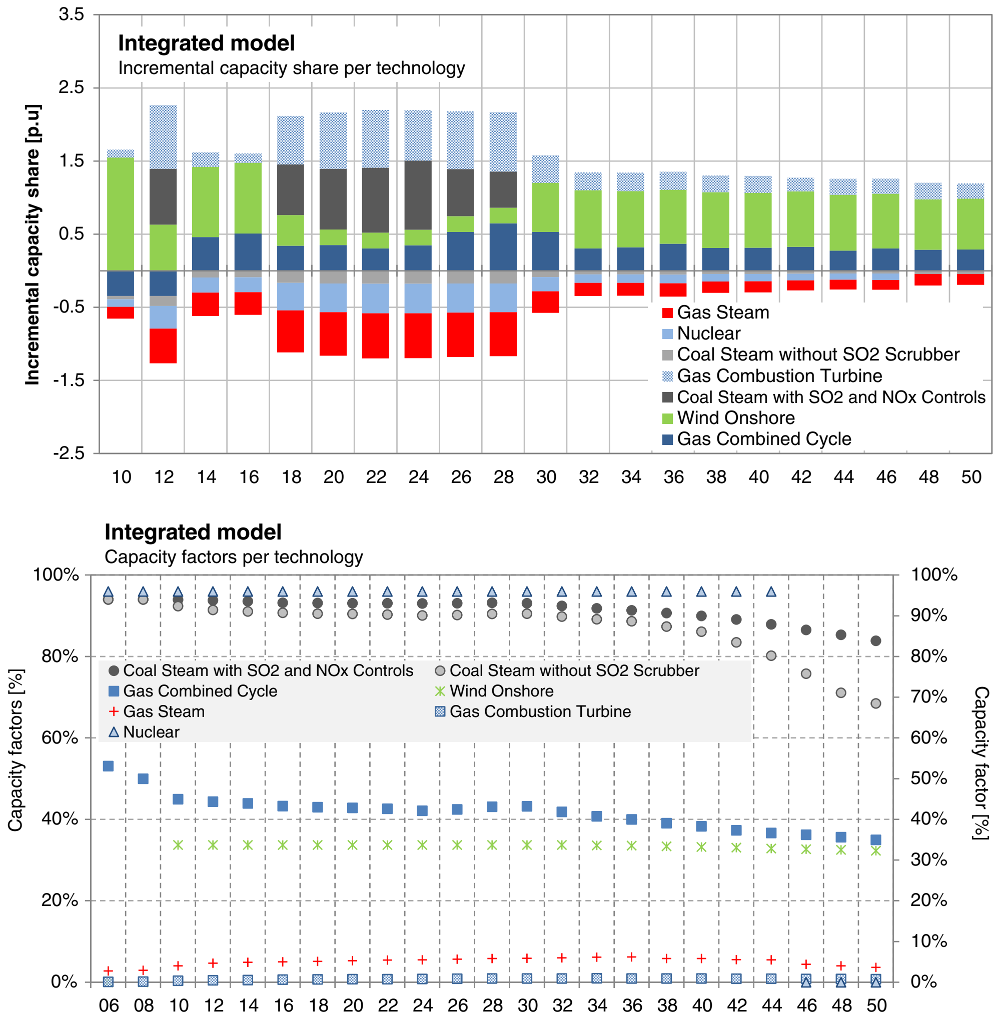

Fig. C.12. Annual incremental capacity share (a) and annual capacity factor (b) by technology type over time.

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. Fig. C.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.[27] Results show that capacity credit decreases over time, with a value of 13% by 2050 compared to 17% in 2010 (see Fig. C.13b). Results also show that the capacity credit of wind decreases as cumulative capacity increases over time (see Fig. C.13c), indicating that its incremental contribution to security of supply decreases.

C.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 (see Fig. C.14). According to the model, the electricity price for the New England region experiences 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.[28] 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 Fig. C.11c above).

[27] 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.

[28] Although oil price index is available from the economy-wide CGE model simulations, it is of no relevance in our analysis given the marginal participation of oil-fired electric generation in the US.

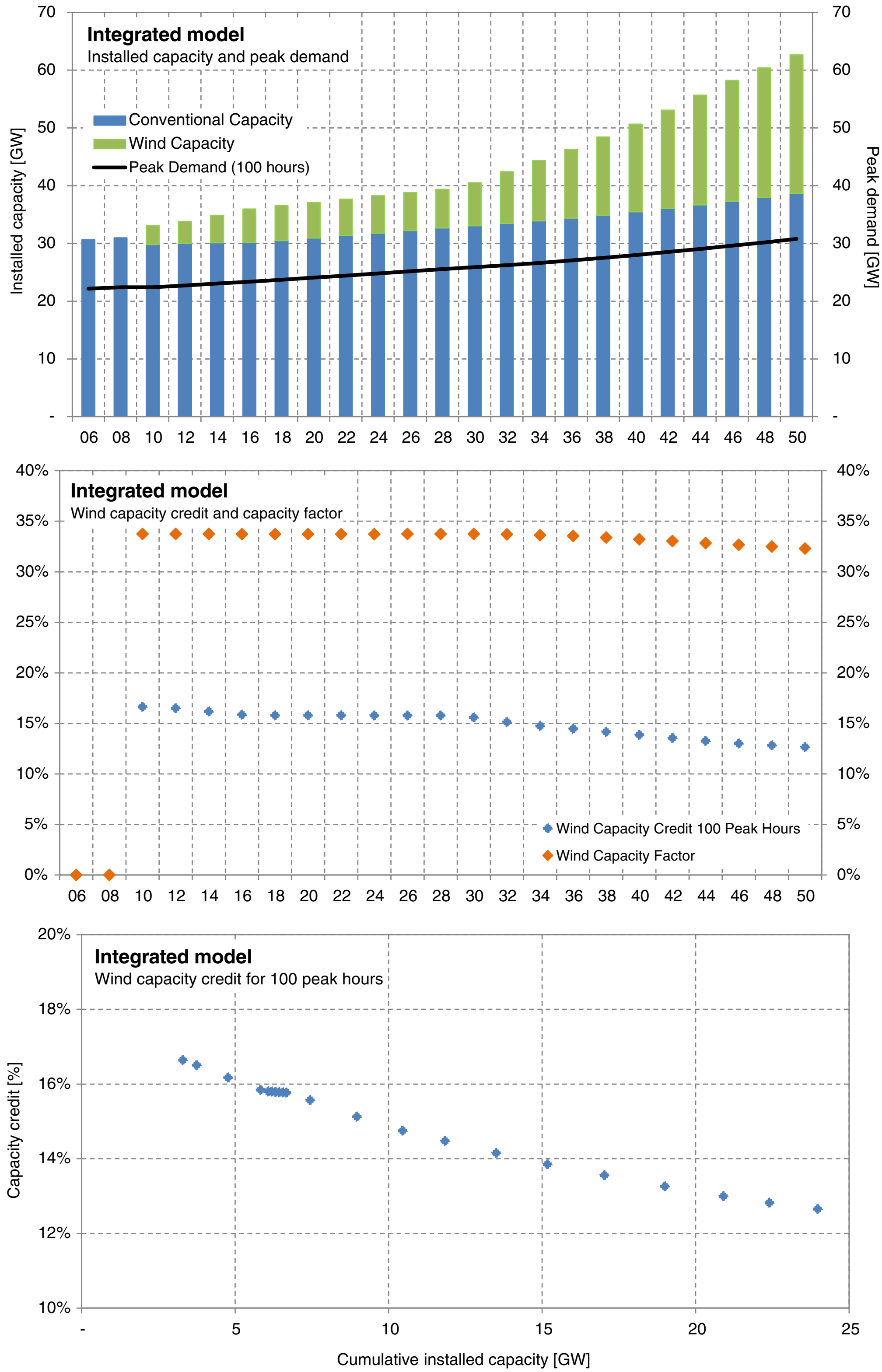

Fig. C.13. Installed capacity and average peak demand over 100 peak hours over time (a), wind capacity credit over 100 peak hours over time (b), and wind capacity credit as a function of installed capacity (c).

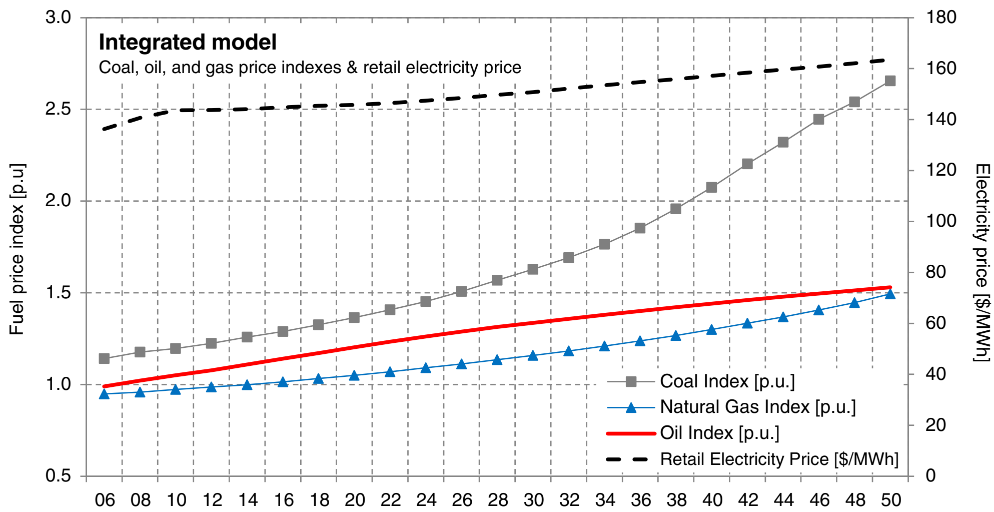

Fig. C.14. Fuel index price and retail electricity price from years 2006 to 2050.

Appendix D. Sensitivity analyses of TD model

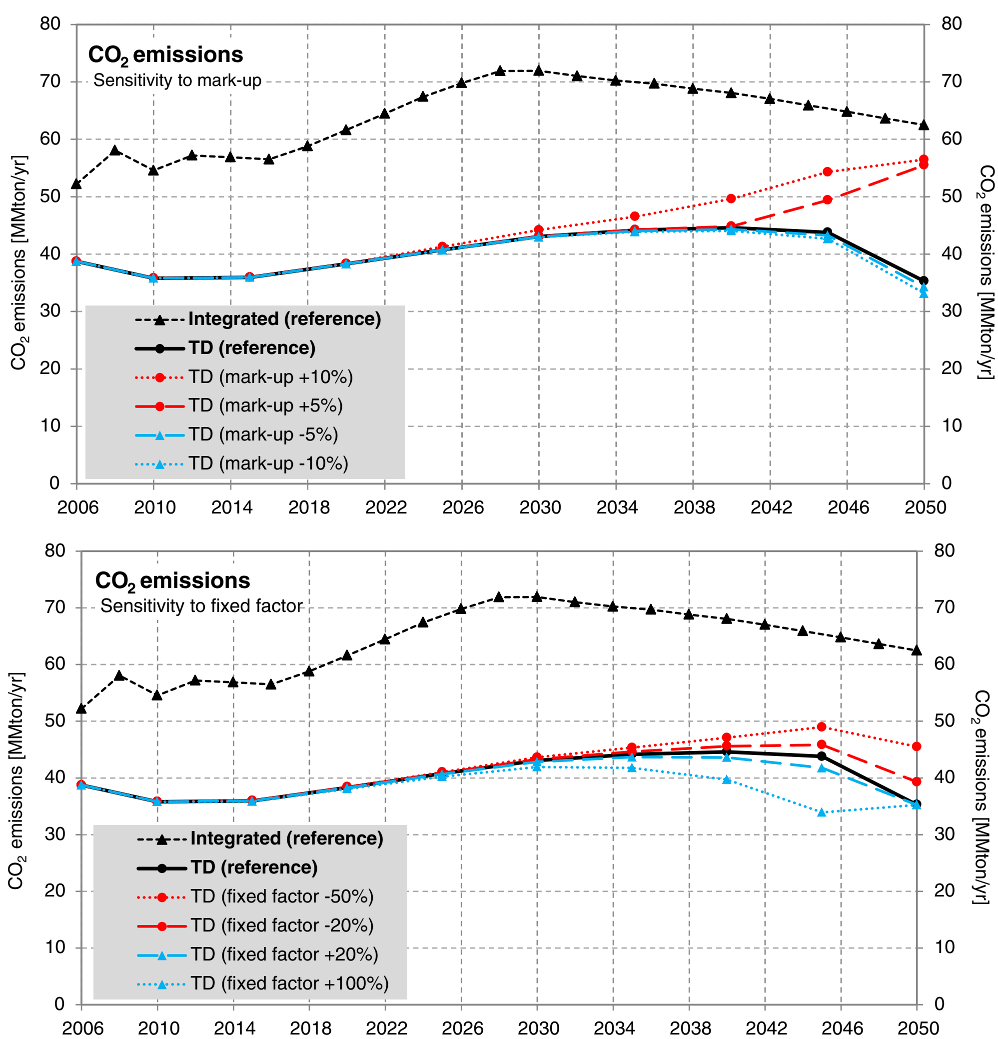

Fig. D.15. CO_2 emissions of electricity sector from years 2006 to 2050 for New England region. Sensitivity to mark-up factor (a) and sensitivity to fixed factor (b). Results from TD version compared to integrated model results.

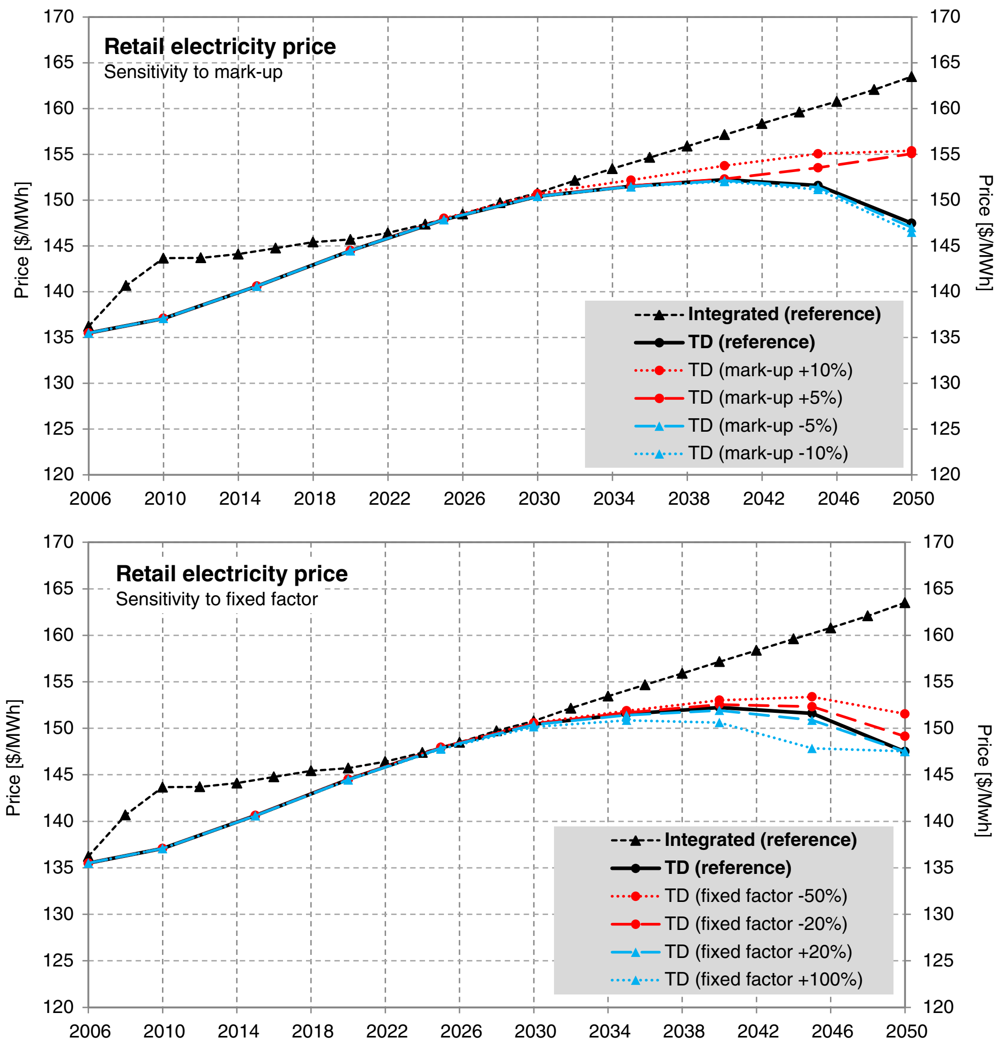

Fig. D.16. Retail electricity prices from years 2006 to 2050 for New England region. Sensitivity to mark-up factor (a) and sensitivity to fixed factor (b). Results from TD version compared to integrated model results.

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