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The effect of environmental policies on risk reductions in energy generation

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We demonstrate that environmental policies can decrease the risks in energy generation for private investors when several renewable technologies are simultaneously triggered. This is because diverse renewable technologies can hedge the intermittent generation of other forms of renewable power. Our study is distinct from previous literature, which has not examined environmental policies through a risk-reduction analysis, or has only considered a few technologies—such as wind and solar—when analyzing risk-reduction benefits. This paper is important, as environmental policies can be justified not only due to environmental benefits, but also economically from a risk-reduction perspective by using basic diversification gains.

1. Introduction

"*In order to fulfill my solemn duty to protect America and its citizens, the United States will withdraw from the Paris Climate Accord.* [...] *This includes ending the implementation of the nationally determined contribution and, very importantly, the Green*

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Climate Fund, which is costing the United States a vast fortune." (June 2017 Statement by President Donald Trump on the Paris Climate Accord—White House.)

It is well-known that detractors of environmental policies—which promote energy production based on environmentally friendly technologies—argue that renewable energy production is not economically efficient from a private investing perspective. These views only analyze the economic perspective of pure cost minimization. This study demonstrates that environmental policies can also provide economic benefits in terms of decreasing risk when multiple renewable technologies are used simultaneously.

We use a model of optimal expansion planning for electricity production of a private investor, under environmental policies, where costs and risks are considered. In the model, new generating plants can be based on diverse renewable technologies (e.g. geothermal, small hydro, biomass, wind, hydro-reservoirs, run-of-the-river and solar technologies) and/or non-renewable technologies (e.g. coal, oil and gas technologies). We consider the investment costs of new generating plants, and their operational costs (i.e. maintenance and fuel price costs). Risks are not only related to economic uncertainty (e.g. volatility of fossil fuel prices and changes in energy demand), but also to unexpected financial costs associated with unsatisfied energy needs that are induced by renewable generation intermittency (e.g. penalties for unmet demand and the use of costly generation reserves to reduce generation intermittency).

The model also includes several characteristics of modern energy systems. First, we explicitly consider the penalties applied when electricity demand remains unsatisfied.[1] Second, we include the use of (and costs associated with) generation reserves (i.e. backup generating capacity) to deal with the intermittency risk of renewable generation (including, as in reality, the reaction speed of such reserves). Third, we consider the possibility that an unexpected contingency may occur in the generating plants when using these reserves, such as the sudden failure of a generator, as modeled by Joskow and Tirole (2007) and Gowrisankaran et al. (2016). Fourth, we consider the use of demand-side services (DSS), in which the option exists for demand-shifting (i.e. moving a certain amount of demand from one hour during a day to another using economic incentives). Fifth, we allow for the possibility of forecasting weather conditions on an hourly basis to consider potential forecasting errors in using system reserves.

The model also characterizes a *basic* diversification effect while considering diverse types of risks that may affect energy generation. If we decompose the electricity supply into different generating technologies, each technology can be observed as an asset within an energy-generation portfolio. Therefore, given that environmental policies induce an increase in the installed capacity and generation of *new* forms of renewable energy production (e.g. energy plants based on small hydro, solar photovoltaic (PV), wind, biomass, geothermal and concentrated solar power (CSP), amongst others), this induces an increase in the diversification of energy production. Thus, in a diversified energy portfolio, each generating technology can be used to *hedge* the risks of other technologies used for energy production, which induces a risk reduction in the whole energy system.

Consequently, we demonstrate that when implementing environmental policies provides a combination of traditional and *new* non-conventional technologies for energy production, this can decrease generation risks through basic diversification benefits. This result is highly relevant, as the implementation of environmental policies can be justified from both environmental and economic perspectives, given the decrease in risk for private investors.

We apply the model to a real case of electricity-production planning. The objective in applying this model is to provide an example of implementation and analyze potential expansion planning under environmental policies, which can be used as a guide in applying the model to other countries or regions. We use the Chilean Central Interconnected System (CIS) to determine optimal generation planning for the year 2025. In this implementation, we use information (and installed capacity) up to December 2014 from the Chilean CIS. We also use a unique dataset of *weather conditions*, which are responsible for the renewable generation intermittency that affects electricity production.

As previously explained, our work indicates that when new forms of renewable power are used due to the implementation of an environmental policy, the intermittent generation of a given renewable technology can be hedged with other forms of renewable power. For instance, we observe that small hydro-power exhibits the lowest average production between 04:00 and 05:00, but high wind-generated energy is available at that time. Additionally, although solar PV generation is highly attractive when producing energy at noon, since solar radiation is at a maximum, no solar generation is available at night. Nevertheless, an increase in availability from small hydro and wind generation, which begins to increase after 18:00, compensates for a lack of nightly renewable production from solar PV plants. Further, biomass and geothermal energy-based plants generate stable electricity (e.g., Perez-Navarro et al., 2010; Heydari and Askarzadeh, 2016; Kulasekara and Seynulabdeen, 2019), which can also address the intermittency of other forms of renewable generation.

Thus, our study differs from previous literature, in which only a few renewable technologies are analyzed in terms of the correlation between their generated outputs. Generally, only the risk-reduction benefits from the interaction between wind and solar renewable generation are examined (Graabak and Korpås, 2016), instead of the hedging advantages gained when *several* renewable and non-renewable technologies produce energy simultaneously, as in our study.

We also demonstrate that increasing renewable technologies due to environmental policies can hedge changes in electricity demand, which is also stochastic. As an example of such hedging interaction in the implementation of the model,

[1] Countries apply penalties when energy demand is not covered to avoid energy supply interruptions (e.g., Losa and Bertoldi, 2009). This is because insufficient electricity can negatively affect a country's current economic performance and future economic development.

on a typical Chilean day, electricity demand is high at around 22:00, when there is also high generation availability from small hydro technology (rivers receiving snowmelt water from the Andean Mountains). In addition, on a typical Chilean day, there is, on average, high electricity demand between 12:00 and 14:00, which coincides with the highest availability of solar generation. These characteristics of renewable technologies (and other behaviors of renewable plants) can also be found in other countries and regions, and the model could thus also be implemented there.

Diverse environmental policies can be applied for energy production, including penalties and/or carbon taxes, among others (Stern, 2008; Harstad, 2012a, 2012b; Marron and Toder, 2014; Diaz et al., 2020). Although our work does not aim to analyze all policy tools, as a policy exercise we present the implementation of two of them, and evaluate them from the model's perspective. Thus, in this policy exercise, (i) we enforce a policy target of a minimum level of renewable generation through a strong penalty; and (ii) we impose a carbon tax. This policy analysis is relevant because private investors can evaluate the effect of regulations from two perspectives: the impact of environmental policies in terms of reducing the risk of energy production; and the financial costs associated with such regulations that are used to reach a given renewable generation goal.

The remainder of this paper is organized as follows: Section 2 presents a literature review, while Section 3 describes the model. Section 4 provides an example in which the model is implemented for optimal electricity-generation planning under environmental policies. Section 5 reports the main results from this implementation and a policy exercise; Section 6 concludes.

2. Literature review

To the best of our knowledge, this study is the first endeavor to analyze environmental policies' risk-reducing effects when multiple renewable and non-renewable technologies are used simultaneously. Nevertheless, our study is associated with previous literature in both engineering and economics.

Optimal expansion planning in the electricity sector has traditionally occurred through purely minimizing costs (e.g., Neuhoff et al., 2008; Steffen and Weber, 2013; Eide et al., 2014). This type of expansion planning reflects only the first moment of the stochastic process regarding the costs involved in energy production. However, expansion planning can also be analyzed from a cost-risk perspective that considers the higher moments in the cost distribution. A cost-risk perspective recognizes that electricity generation can be risky, as it is affected by several variables that can change over time. Bar-Lev and Katz (1976) first introduced diversification in planning for expanded generation, in which both costs and risks are considered; Awerbuch and Berger (2003), Awerbuch (2013), Jansen et al. (2006), Delarue et al. (2011) and Inzunza et al. (2016) have more recently incorporated this concept into their works, among others.

Operational aspects relative to the security of supply must also be considered to ensure optimal expansion planning for electricity generation. For instance, Huang and Wu (2008) and Gotham et al. (2009) developed models for electricity-generation planning that incorporate operational constraints under intermittent renewable generation. Currently, since there is a significant concern regarding security of supply, given the growth of renewable generation, De Jonghe et al. (2011), Pérez-Arriaga and Battle (2012), Chávez et al. (2014) and Inzunza et al. (2016) suggest that additional constraints have to be considered in order for energy production stability to be maintained, such as higher levels of generation reserves, which we also include in our study. In addition to supply security, flexibility requirements are becoming important with higher volumes of renewable generation, because of ramp rate limits and the time taken to start up and shut down power units, among the other flexibility limitations of conventional plants (see, e.g., Moreno et al., 2017b).

Our paper is also associated with studies in that analyze the importance of renewable intermittency (Baker et al., 2013) and those that observe how the time-varying dynamics of renewable energy generation are evaluated from an economic perspective (Denholm and Margolis, 2007; Borenstein, 2008; Joskow, 2011; Cullen, 2013; Gowrisankaran et al., 2016). There are also studies in which potential fossil fuel capacity is analyzed to complement large-scale renewables, with (see Lamont, 2008) and without (see Skea et al., 2008 and Campbell, 2011) time-varying generation profiles for renewable generation.

Our paper relates to an analysis of alternative solutions to the risk of intermittent renewable generation, and especially in terms of the use of energy storage and transmission. On the one hand, the risk of such generation can be mitigated by storing energy. For example, Pommeret and Schubert (2019) present a dynamic model of the optimal transition from generating energy from fossil fuel to renewable power, which considers energy storage and the intermittent nature of renewable energy production. Zerrahn et al. (2008) demonstrate that the levels of energy storage required for renewable generation are not as high as we thought. In fact, Zerrahn et al. (2008) find that energy storage needs are considerably lower, and they propose a potential solution that combines energy storage and renewable curtailment. For the particular case of Chile, Moreno (2017a) and Diaz et al. (2019) show some of the potential benefits of storage systems for dealing with the high penetration of renewable generation in an efficient fashion. Interestingly, and in line with our paper, Diaz et al. (2019) examine the benefits of storage plants from the perspective of risk-averse market participants, finding that greater storage capacity can significantly contribute towards increasing the participation of renewable power (such as the use of wind and solar technologies).

Alternatively, increasing the energy transmission between countries and/or regions can also mitigate the risk of intermittent renewable generation (e.g., Abrell and Rausch, 2016). The increase in the use of transmission infrastructure highly connects with our paper's objectives, as the former is also a form of diversification. In the case of insufficient energy supply in a given area due to intermittent renewables, excess energy generated from other regions might be used. Moreover, energy storage and transmission can be complementary in addressing issues with intermittent renewable generation (e.g., Neetzow et al., 2018).

Our paper differs from prior works, in that we use diversification as a tool to reduce renewable power's impacts on the intermittent energy supply. Moreover, our model considers the use of three additional tools to mitigate intermittency risk: (i) generation reserves, such as having a backup generating capacity to deal with intermittent renewables; (ii) demand shifting, or the option to move a certain amount of demand from one hour during a day to another using economic incentives; and (iii) the possibility of forecasting weather conditions on an hourly basis to consider potential forecasting errors in using system reserves.

Our paper also connects with studies in which different environmental policies are analyzed, but not from a risk-reduction perspective as in our paper (e.g., Stern, 2008; Harstad, 2012a, 2012b; Marron and Toder, 2014). Additionally, our paper relates to studies that investigate the design of optimal mechanisms for reaching a specific renewable policy target (e.g., McLure, 2014; Murray et al., 2014; Acemoglu et al., 2016; Golosov, 2014).

Therefore, and as previously explained, we focus on a different but important objective from literature: our study aims to understand the economic benefit from decreasing the risks of energy production as induced by environmental policies when diverse renewable technologies are a part of the system.

3. The model

3.1. Optimal expansion planning

In this section, we describe the model of optimal expansion planning for future electricity generation under environmental policies. In the model, a carbon reduction policy is implemented in order that a renewable policy target can be reached by year τ. Let us assume that there is an electricity-generating company of a private investor, who needs to make a decision regarding investing in a portfolio of I different technologies, which are available for building generating plants for electricity production. The electricity-generating company is part of an electricity market that is perfectly competitive; thus, the private investor is a price taker of the electricity price. Each generating technology, $i \in \{1, 2, \dots, I\}$, has particular characteristics in terms of investment costs, operational costs and current installed capacity, amongst other features.

The company is expected to supply electricity in each hour $j \in \{1, 2, \dots, 8760\}$ of the year (i.e. 365*24=8760 h). The electricity generated on an hourly basis by technology i depends on the installed generating capacity, cap_i, in megawatts (MW), and the characteristics of the technology in terms of its ability to generate electricity in each particular hour of the year (e.g. plants based on solar PV generation have greater availability in summer than winter).

There is a set of states that describes the potential conditions of generation in each hour of the year for all plants based on the different technologies. State $s \in \{1, 2, \dots, S\}$ is characterized by a group of stochastic variables, which have a joint probability of occurrence $p(s)$. These stochastic variables reflect changes in economic features (e.g. fossil fuel prices, levels of customers' electricity demand and/or any other stochastic economic variable that is relevant for the private investor) and in renewable generation availability, which is affected by the variability in climate conditions (e.g. solar radiation, wind power and hydrological).

As in modern generating systems, the model considers the implementation of demand-side services (DSS). DSS represent the possibility of moving a certain amount of energy required by customers from one hour to another. Customers can move their electricity consumption to a particular time after receiving certain signals. The implementation of DSS has several purposes: to switch a part of the electricity consumption from peak hours with high electricity demand; to allow the efficient use of renewable technologies for electricity generation (since some renewable technologies generate more electricity during certain hours of the day); and to optimize the use of the complete generating system in the case of unexpected events. Nevertheless, the implementation of DSS is costly due to the use of economic incentives to modify the demand behavior of customers (e.g. the electricity company might reduce the price of electricity if customers shift their demand behavior). Thus, a decrease (increase) in the amount, D_j^- (D_j^+), of electricity demand is associated with a cost dc^- (dc^+).

Let $a \in \Gamma$ be a possible planning decision, where Γ is the set of all potential planning decisions, which can be made in terms of the expansion of new generating plants based on different technologies. Decision a not only considers the installed capacity of each generating technology, cap_i, but also *future* optimal operational decisions on an hourly basis, in each state of the economy. Thus, decision a considers the optimal generation, $g_{i,j}(s)$, in each hour j when using technology i, where $0 \le g_{i,j}(s) \le cap_i$. In addition, decision a considers optimal demand switches for the DSS, $D_j^-(s)$ and $D_j^+(s)$.

Decision a is key for electricity production, as it may generate a lost load, $LL_j(s)$, in a given hour, j, in some states, in which there is not enough energy generation to supply the total electricity demand, $D_j(s)$, where $LL_j(s)$ is:

$$LL_j(s) = D_j(s) + D_j^+(s) - D_j^-(s) - \sum_{i \in I} g_{i,j}(s). \tag{1}$$

The lost load is costly, since there is a penalty, $voll$, when the demand is not covered, with $voll = 0$ in the case where $LL_j(s) < 0$. This penalty is imposed by the regulator on the private investor to avoid energy supply interruptions. This is because insufficient electricity generation can (directly and/or indirectly) negatively affect how well countries function in terms of health and education services, industrial production, consumption, telecommunications, exchange of goods, financial systems and security structures, to name but a few examples.

Let $EP(s)$ be the economic incentives imposed by environmental policies regarding the use of renewable technologies for electricity production. For instance, $EP(s)$ could be a carbon tax, which depends on carbon emissions per generating technology, or a penalty imposed if the demand supplied by renewable electricity generation in the target year does not reach a particular minimum level.

Let INV_i be the annuitized investment cost of having installed capacity cap_i. In addition, let $VOM_i(s)$ be the operational cost of electricity production using technology i when in state s, which includes fuel prices (the operational cost independently includes the maintenance cost and the fuel price cost, in the case of technologies that use fuel). Thus, the total cost of electricity generation per year in state s, $C(s)$, is given by:

$$\begin{aligned} C(s) &= EP(s) + \sum_{j\in J} D_j^-(s)\cdot dc^- + \sum_{j\in J} D_j^+(s)\cdot dc^+ + voll\cdot\sum_{j\in J} LL_j(s) \\ &\quad + \sum_{i\in I} INV_i\cdot cap_i + \sum_{i\in I}\sum_{j\in J} VOM_i(s)\cdot g_{i,j}(s). \end{aligned} \tag{2}$$

Eq. (2) shows that the total cost comprises five components: economic incentives induced by environmental policies, the costs associated with the DSS, the potential cost associated with penalties imposed for unsatisfied energy demand, the investment cost and the operational cost. It is important to observe in Eq. (2) that the annuitized investment cost has to be paid on the installed capacity of all technologies; hence, it is costly to have oversized generating units.

As mentioned in the introduction, optimal planning for electricity generation is based on a portfolio analysis, incorporating both costs and risks so as to reach an optimal decision. In the model, the risk exposure of the energy production is calculated using the conditional value-at-risk, $CVaR_\alpha$, with confidence level α. $CVaR_\alpha$ captures the expected cost of total energy production in the worst α% of cases. Therefore, optimal planning for electricity generation under environmental policies, from a cost–risk perspective, is obtained by solving the following optimization problem, while considering a level of risk given by $CVaR_\alpha^*$:

$$\arg\min_{a} \sum_{s=1}^{S} C(s)p(s) \tag{3}$$

s.t.

$$\frac{1}{1-\alpha}\sum_{C(s)\geq VaR_\alpha} C(s)p(s) = CVaR_\alpha^* \tag{4}$$

$$0 \leq g_{i,j}(s) \leq cap_i \tag{5}$$

$$\sum_{\jmath=j-12}^{j+12} D_\jmath^+(s) - \sum_{\jmath=j-12}^{j+12} D_\jmath^-(s) = 0 \tag{6}$$

$$D_j^-(s) \leq \mathrm{q}^-\cdot D_j(s) \tag{7}$$

$$D_j^+(s) \leq \mathrm{q}^+\cdot D_j(s). \tag{8}$$

Expression (3) reflects that the private investor maximizes expected profits by minimizing the expected cost of the generating system. This is because the private investor is part of a competitive electricity market (i.e. the private investor is a price taker of the electricity price); thus, potential revenues from selling the electricity are not affected by the investor's decisions. The constraint in Eq. (4) is related to the level of risk exposure of the system. Eq. (4) imposes that a potential optimal decision, $\tilde{a}\in\Gamma$, should deliver a level of risk, $CVaR_\alpha^*$, where VaR_α is the value-at-risk of the system cost, with confidence level α.[2]

The constraint in (5) reflects that electricity generation through technology i cannot be higher than the installed capacity in any hour, j, of year τ. The constraint in Eq. (6) imposes that demand changes due to demand shifts are balanced within a time window of 24 h. The constraints in (7) and (8) impose that demand shifts can only change within given limits that depend on the electricity demand level, where q^- and q^+ are the maximum proportions of demand in any hour that can be reduced and augmented, respectively.

In the decision problem described in expressions (3)–(8), the constraint related to risk in Eq. (4) is not linear. A non-linear constraint can make large optimization problems difficult to solve. Nevertheless, Rockafellar and Uryasev (2000, 2002) and Krokhmal et al. (2002) show that, in financial optimal allocation problems, risk constraints based on the $CVaR$ can be formulated in a linear programming problem through the inclusion of auxiliary variables and additional linear constraints. This is possible because the $CVaR$ is a convex and coherent measure of risk in the sense that it satisfies the properties of

[2] The VaR_α in the model is the level of large costs which could occur with probability α.

monotonicity, sub-additivity, homogeneity and translational invariance (see Artzner, 1999). Thus, following Rockafellar and Uryasev (2000, 2002) and Krokhmal et al. (2002), we can rewrite the optimization problem in expressions (3)–(8) as:

$$\arg\min_{z,\ a} \sum_{s=1}^{S} C(s)p(s) \tag{9}$$

s.t.

$$z + \frac{1}{1-\alpha}\sum_{s=1}^{S} \delta_s p(s) \leq CV \tag{10}$$

$$C(s) - z \leq \delta_s \tag{11}$$

$$0 \leq \delta_s, \tag{12}$$

$$0 \leq g_{i,j}(s) \leq cap_i \tag{13}$$

$$\sum_{\jmath=j-12}^{j+12} D^{+}_{\jmath}(s) - \sum_{\jmath=j-12}^{j+12} D^{-}_{\jmath}(s) = 0 \tag{14}$$

$$D^{-}_{j}(s) \leq \mathrm{q}^{-} \cdot D_j(s) \tag{15}$$

$$D^{+}_{j}(s) \leq \mathrm{q}^{+} \cdot D_j(s) \tag{16}$$

where z is an auxiliary variable which is part of the objective function in (9), and $\delta_s \in \{\delta_1, \delta_2, \dots, \delta_S\}$ is also an auxiliary variable that reflects the rightward deviation of the costs with respect to z in state s. The risk tolerance level in the *CVaR* is given by *CV*, which represents the α-*CVaR*'s upper bound of system costs. The constraints in (10) and (11) represent a two-segment piecewise linear function which computes δ_s only in the case of higher costs than z (see also the condition in expression (12)). As shown in Rockafellar and Uryasev (2000, 2002) and Krokhmal et al. (2002), the value of z is the VaR_α in the optimal solution. Therefore, the constraint in Eq. (10) provides a lower bound for the expected value of violations of the system costs which are higher than the VaR_α, in which this expected value of violations of the system costs is indeed the $CVaR^*_\alpha$.

Before moving to the next section, where we will explain how potential environmental policies are included in the model, it is important to notice that the assumption of a single private investor (which was stated at the beginning of this section) is not crucial. In fact, in the case of multiple investors, if they are price takers and have access to a financial market that is complete (which can be used to hedge any potential source of uncertainty), the optimal planning of all investors can still be modeled as a single-investor problem. Thus, if different investors minimize their expected generation costs subject to a given level of *CVaR*, this is equivalent to a single optimization problem that minimizes the sum of the objective functions of all investors. This is possible because the *CVaR* is a coherent measure of risk, as explained previously, which has the properties of monotonicity, sub-additivity, homogeneity and translational invariance (see Ralph and Smeers, 2010; Ehrenmann and Smeers, 2011; and Munoz et al., 2017).

3.2. Potential environmental policies

As mentioned in the introduction, there are diverse environmental policies which can be implemented. Since the objective of our paper is not to analyze all potential environmental regulations, but rather to show the intuitions behind the impact of environmental policies in terms of reductions in the generation risks, we only examine the effects of two of them.

Minimum level of renewable generation: The first potential environmental policy used in this paper is a strong penalty, which is applied if a target for renewable generation is not reached. Under this policy, there is a fixed penalty K, charged at the end of the year if the renewable generation supply does not reach a predetermined fraction, $Target^R$, of the total demand for the period. Thus, under this environmental policy, $EP(s)$ in Eq. (2) is:

$$EP(s) = \begin{cases} K & Target^R > \dfrac{\sum_{i^R=1}^{I^R}\sum_{j=1}^{8760} g_{i^R,j}(s)}{\sum_{j=1}^{8760} D_j(s)} \\[2ex] 0 & Target^R \leq \dfrac{\sum_{i^R=1}^{I^R}\sum_{j=1}^{8760} g_{i^R,j}(s)}{\sum_{j=1}^{8760} D_j(s)}, \end{cases} \tag{17}$$

where $i^R \in \{1, 2, \dots, I^R\}$ is an indicator for the renewable technologies, with $I^R \leq I$.[3] Thus, this first environmental policy involves a *one-off penalty*, which is applied at the end of each period. Notice that this policy resembles a renewable portfolio standard (RPS) policy (see, e.g., Palmer and Burtraw, 2005; Go et al., 2016; and Lyon, 2016). The RPS is a policy that imposes a minimum percentage of electricity that must be produced by renewable technologies, where a penalty is applied if that percentage is not reached. This type of environmental policy has been planned or established in several countries, including Italy, Denmark, Belgium, Australia, Austria, Sweden, the United Kingdom and the United States (see Fischer and Newell, 2008).

Carbon tax: The second environmental policy analyzed is a carbon tax. Let us assume that there is a potential carbon tax of q dollars per ton of carbon dioxide equivalent (CO_2e) emissions (see, e.g., Fischer and Newell, 2008 and Diaz et al., 2020).[4] Therefore, under this environmental policy, $EP(s)$ in Eq. (2) is:

$$EP(s) = \sum_{i \in I} \sum_{j \in J} q \cdot em_i \cdot g_{i,j}(s), \tag{18}$$

where em_i denotes the CO_2e emission factor for technology i. Thus, this second environmental policy is a *per-carbon-unit tax*, which is paid whenever energy production involves CO_2e emissions. Consequently, this policy incentivizes the reduction of CO_2e emissions, which strongly affects fossil fuel technologies because the carbon tax makes fossil fuel power relatively more expensive than renewable generation. This type of policy has been implemented in several countries, for example, Ramstein et al. (2019) report that there are 29 carbon taxes around the world, primarily implemented on a national level.

3.3. Intermittency of renewable generation

Electricity generation based on renewables is generally intermittent, since it depends on exogenous factors such as solar radiation, wind power and/or the hydrological situation. To consider the potential intermittency of renewable generation, the maximum capacity of electricity generation using the renewable technology i^R, cap_{i^R}, is reduced by a stochastic capacity factor $CF_{i^R,j}(s)$ in each hour j, where $0 \leq CF_{i^R,j}(s) \leq 1$. The stochastic capacity factor, $CF_{i^R,j}(s)$, reflects the variability of renewable generation due to weather conditions. Thus, the potential generation, $g_{i^R,j}(s)$, of technology i^R is constrained as follows:

$$g_{i^R,j}(s) \leq CF_{i^R,j}(s) \cdot cap_{i^R}, \tag{19}$$

where cap_{i^R} is the planned installed capacity for this technology in year τ.

In the case of generation based on hydro-reservoir technology, i^{HR}, we impose that the maximum generating capacity must be related to water inflows per hour in reservoirs, $inf_{i^{HR},j}(s)$, which are part of the hydrological conditions that describe state s. As such, electricity generation from hydro-reservoir technology, $g_{i^{HR},j}(s)$, is constrained by:

$$\frac{g_{i^{HR},j}(s)}{\eta} = inf_{i^{HR},j}(s) \cdot \frac{cap_{i^{HR}}}{cap^{curr}_{i^{HR}}} - \left(v_{i^{HR},j}(s) - v_{i^{HR},j-1}(s)\right) - v_{i^{HR},j}(s) \cdot \lambda - sp_{i^{HR},j}(s), \tag{20}$$

$$v^d \cdot \frac{cap_{i^{HR}}}{cap^{curr}_{i^{HR}}} \leq v_{i^{HR},j}(s) \leq v^u \cdot \frac{cap_{i^{HR}}}{cap^{curr}_{i^{HR}}} \tag{21}$$

and

$$v_{i^{HR},8760}(s) = \frac{v_{i^{HR},0}(s)}{(1+\lambda)^{8760}}, \tag{22}$$

where η is the generating efficiency (i.e. the rate of inflow to generation) of the hydro technology (in MWh per cubic meter), $cap_{i^{HR}}$ is the planned installed capacity for this technology in year τ, $cap^{curr}_{i^{HR}}$ is its current installed capacity, $v_{i^{HR},j}(s)$ is the volume of water in reservoirs in hour j and state s, λ is a factor used to consider the loss of stored water due to evaporation and/or seepage in reservoirs, and $sp_{i^{HR},j}(s)$ is the water lost through spillages in hour j in state s.[5] In addition, v^d and v^u are the lower and upper bounds of the water stored in reservoirs, respectively, in relation to the current installed capacity.

In Eqs. (20) and (21), the values of $inf_{i^{HR},j}(s)$, v^d and v^u are multiplied by the ratio $cap_{i^{HR}}/cap^{curr}_{i^{HR}}$ in order to model the idea that, as more hydro plants are added to the system, these variables should grow proportionally. Constraint (20) shows that electricity generation using i^{HR} has to be balanced in terms of the water available in reservoirs, since $g_{i^{HR},j}(s)$ can modify the volume of stored water. Constraint (21) imposes that water stored in reservoirs stays within specific bounds over the whole year. In addition, Eq. (22) is a constraint related to the use of hydrological resources, which is used in generation planning with the aim of keeping the initial and final levels (per annum) of stored water in reservoirs the same.

[3] The policy target is based on the goal of satisfying electricity demand through renewable generation, and not on the proportion of installed renewable technology capacity. This is because, when a plant is built to *potentially* generate energy with technology i^R and capacity cap_{i^R}, it may be the case that no electricity is produced by this plant in the entire year.

[4] CO_2e is a term describing different greenhouse gases through a common unit. For any quantity and type of greenhouse gas, CO_2e refers to the amount of CO_2 which would have the equivalent impact on global warming.

[5] The value of $sp_{i^{HR},j}(s)$ is also one of the operational decisions made in each hour j and state s.

3.4. Operational constraints on the rate of change in the level of electricity generation

Since the focus of the model is on determining the total installed capacity of the generating technologies, the installed capacity for each technology is decided in an aggregate fashion. Nonetheless, in order to model the operation of a real system on an hourly basis, it is necessary to quantify the number of online units connected to the system during each hour in state s. Suppose that expansion planning for the electricity supply considers having N_i generating units for technology i in year τ. Let $n_{i,j}(s)$ be the number of online generating units for technology i connected to the system in hour j and state s, with $n_{i,j}(s) \leq N_i$.

Let us assume that the maximum output generated by one unit using technology i is $\bar{P}_i$; thus, $n_{i,j}(s) \cdot \bar{P}_i \leq cap_i$ and $N_i \bar{P}_i \equiv cap_i$. Let us also assume that generating plants have a lower bound on their electricity generation (e.g. due to combustion stability issues in fossil-fuel-based generating plants). Thus, let $\underline{P}_i$ be the minimum power output of one generating unit using technology i, where $\underline{P}_i \leq \bar{P}_i$. Therefore, $n_{i,j}(s)$ should satisfy:

$$n_{i,j}(s) \cdot \underline{P}_i \leq g_{i,j}(s) \leq n_{i,j}(s) \cdot \bar{P}_i. \tag{23}$$

Moreover, and as in reality, let us assume that electricity production cannot increase or decrease drastically.[6] Let t_i be the minimum time it takes a generating unit using technology i to increase its power output from $\underline{P}_i$ to $\bar{P}_i$. Thus, the rate of change of the power output of this generating unit is $\rho_i = (\bar{P}_i - \underline{P}_i)/t_i$, which is known as the 'ramp rate'. Therefore, in terms of ramp rates, we constrain the difference in output between two consecutive hours as follows:

$$g_{i,j}(s) - g_{i,j-1}(s) \leq \min\left(n_{i,j}(s), n_{i,j-1}(s)\right) \cdot \rho_i + \left(n_{i,j}(s) - n_{i,j-1}(s)\right) \cdot \underline{P}_i \tag{24}$$

$$g_{i,j-1}(s) - g_{i,j}(s) \leq \min\left(n_{i,j}(s), n_{i,j-1}(s)\right) \cdot \rho_i + \left(n_{i,j-1}(s) - n_{i,j}(s)\right) \cdot \underline{P}_i. \tag{25}$$

Eq. (24) (Eq. (25)) reflects the fact that, in a ramping-up case (ramping-down case), the change in generation cannot be larger than the ramping capability of the units that are connected during two consecutive hours plus the output of the units that are connected (disconnected). It is assumed that units are both connected and disconnected at their minimum output, which is a conservative assumption.

3.5. The use of generation reserves

The model considers the use of operational reserves to adjust possible generation imbalances due to renewable generation intermittency or a potential failure in a generating plant. There are two main types of operational reserves: spinning reserves and standing reserves. Spinning reserves correspond to the additional generating capacity that can be used by increasing the power output of electricity generators that are already connected to the system. Letting $R^{sp}_{i,j}(s)$ be the spinning reserves in year τ for technology i in hour j and state s, such reserves should respect the following constraints:

$$R^{sp}_{i,j}(s) + g_{i,j}(s) \leq n_{i,j}(s) \cdot \bar{P}_i \tag{26}$$

and

$$R^{sp}_{i,j}(s) + g_{i,j}(s) \leq CF_{i,j}(s) \cdot cap_i, \tag{27}$$

where $n_{i,j}(s)$ and $\bar{P}_i$ are as defined in constraint (23). Constraint (26) ensures that the provision of spinning reserves and the output generated by technology i are limited by the maximum generating capacity of online units. Constraint (27) ensures that spinning reserves and electricity generation from technology i do not exceed the generation availability in each hour of year τ.

In contrast to spinning reserves, standing reserves are the extra generating capacity that is not currently connected to the power system (i.e. reserves standing outside the power system).[7] Letting $R^{st}_{i,j}(s)$ be the standing reserves of technology i in hour j and state s, $R^{st}_{i,j}(s)$ is:

$$R^{st}_{i,j}(s) = cap_i - n_{i,j}(s)\bar{P}_i. \tag{28}$$

The model uses reserves for two main events: (i) keeping the system stable after an unexpected contingency such as a failure of a generating plant, and (ii) maintaining the security of the electricity supply after unpredicted changes in the energy generated by renewable technologies (since they can be intermittent) and/or changes in electricity demand.

In the Supplementary Appendix A, we describe additional features of the model related to maintaining the security of the electricity supply. Thus, in that appendix, we describe (i) constraints when considering unexpected contingencies such as the sudden failure of a generator; (ii) constraints related to the post-contingency recovery of energy production; and (iii) the use of weather-forecasting tools to improve the efficiency of renewable generation.

[6] Electricity generation cannot change instantaneously due to, for example, hydraulic transients in water masses in hydro-generation plants, and thermodynamic processes in fossil fuel plants.

[7] In general, only fast-start units, which are based on fossil fuel power, are considered to be standing reserves, since it may take hours or even days to connect other types of units.

3.6. Solution approach

The objective of the model is to obtain optimal planning for future electricity generation under environmental policies, considering the economic risk and the intermittency risk, when multiple renewable technologies are used simultaneously. Thus, we have to solve the optimization problem described in expressions (9)–(16), including all constraints explained in this section as well as those in the supplementary appendix. As a first step in the solution approach, we characterize the stochastic components of the power system through the use of Monte Carlo simulations. Each Monte Carlo simulation describes a state in the year τ, which characterizes *each hour* of the year. For instance, the Monte Carlo simulations should include the stochastic processes followed by fossil fuel prices. They should also include hourly changes in renewable generation availability, which is affected by the variability of climate conditions (solar radiation, wind power and hydrological) and changes in electricity demand. Changes in any of the variables that describe state s of year τ will modify the potential costs related to penalties for unsatisfied demand and operating costs associated with the optimal generation planning.

We split the optimization problem into two connected sub-problems, which are solved simultaneously. The first optimization problem focuses on the initial investment decision (i.e. the types and sizes of new generating plants, which have to be operating at the beginning of target year τ). The first optimization problem also includes the decision over whether to invest in extra installed generating capacity (i.e. in addition to that required to satisfy the *expected* demand) to be used as a backup and, thus, to deal with stochastic changes in the weather variables that characterize the system.

The second optimization problem is formulated so as to make optimal operational decisions (hourly) per generating technology in each Monte Carlo simulation. However, the risk levels in terms of the potential costs obtained from the Monte Carlo simulations cannot be higher than the tolerated *CVaR* (i.e. $CVaR^*_\alpha$ in Eq. (10)). The *CVaR* of the generating costs in year τ is calculated using the distribution of costs obtained from the Monte Carlo simulations, after considering the optimal investment and operational decisions. Thus, the optimal (hourly) operational decisions from the Monte Carlo simulations induce a *feedback effect* on the first optimization problem, as the initial investment decisions consider (and simultaneously affect): the operational costs; costs related to penalties for unsatisfied demand; and the level of the *CVaR* of the generating system. This technique of dividing the original optimization problem into two *connected* sub-problems is the intuition behind Benders' decomposition. Therefore, the model for optimal generation planning is solved by means of Benders' decomposition, so as to tackle the large-dimension problem of expansion planning for electricity generation under environmental policies.

The intuition behind Benders' decomposition can be summarized as 'divide and conquer'. More specifically, Benders' decomposition consists of dividing the optimization problem into two sub-problems: 'master' and 'slave'. In the case of optimal expansion planning of electricity generation, as explained above, the master problem is formulated to optimize the initial investment decision in year τ (i.e. installed capacity per generating technology). Afterwards, Monte Carlo simulations are performed in order to describe diverse scenarios which can happen in year τ. The slave problem is formulated to make optimal hourly operational decisions in each simulation (i.e. the hourly operation of the power system) based on the investment plan obtained from the master problem.[8] Thus, the slave problem takes into account changes in fossil fuel prices, renewable intermittency and variability in electricity demand. In each iteration, Benders' decomposition algorithm guides the master problem based on the dynamics of the slave problem as it progresses towards optimal expansion planning.

4. Model implementation

We implement the model to plan the expansion investments for a real case involving electricity production under environmental policies. As mentioned in the Introduction, such an implementation aims concretely demonstrate the model's use, and thus, to understand environmental policies' impacts on decreasing risk in energy production, when multiple renewable technologies are simultaneously used. This example is valuable because it can be used as a guide for private investors in implementing our model in other countries or regions.

We implement the model for the Chilean CIS, with an expansion planned for future energy production in the year 2025 based on information—including the installed capacity—as of the end of 2014. In this implementation example, we assume that the entire CIS is owned by a single private investor. However, other implementation examples could be used, such as analyzing only a part of the Chilean CIS that has a single owner. In this implementation example, we prefer to assume that the entire CIS is owned by one investor, as we aim to analyze the potential effects from using diverse generating technologies in expansion planning, as is the case in the complete CIS.[9]

We select 2025 as the expansion year for several reasons. Firstly, the Chilean government has a renewable policy target of 20% of electricity demand being satisfied, by 2025, through 'non-conventional' renewable technologies (namely, renewable

[8] The use of Benders' decomposition necessitates having a set of linear slave problems. However, some of the operational constraints imposed in the model are non-linear. In order to make the problem computationally tractable through the use of Benders' decomposition, we transform the non-linear constraints into their linear versions using Taylor expansions and other simplifications. In the Supplementary Appendix A, we provide a detailed mathematical description of these transformations.

[9] Moreover, and as explained at the end of Section 3.1, the optimal planning for multiple investors can be modeled as a single-investor problem if the investors are price-takers and have access to a complete financial market. This is because the *CVaR* is a coherent measure of risk (see Ralph and Smeers, 2010; Ehrenmann and Smeers, 2011; and Munoz et al., 2017).

Table 1
Initial installed capacities as of 2014, capacity factors and upper bounds for future capacities.
In this table, solar PV is solar photovoltaic technology, while solar CSP is concentrated solar power.

	Average capacity factors (a)	Current installed capacity in MW (b)	Proportion of current installed capacity in %	Current installed capacity (effective) in MW (a)*(b)	Proportion of current installed capacity (effective) in %	Upper bound for future installed capacity in MW (c)	Upper bound for future installed capacity (effective) in MW (a)*(c)
Coal	100%	2394	15.8%	2394	21.6%	6000	6000
Oil	100%	2303	15.2%	2303	20.8%	3000	3000
Hydro	44%	4053	26.8%	1773	16.0%	7000	3063
Wind	28%	634	4.2%	179	1.6%	4000	1126
Solar PV	24%	169	1.1%	41	0.4%	2600	630
Liq. Nat. Gas (LNG)	100%	2777	18.3%	2777	25.0%	3000	3000
Run-of-river	52%	1965	13.0%	1016	9.2%	4000	2068
Biomass	85%	504	3.3%	428	3.9%	1000	850
Geothermal	85%	0	0.0%	0	0.0%	200	170
Small hydro	52%	350	2.3%	181	1.6%	800	414
Solar CSP	52%	0	0.0%	0	0.0%	200	104
Non-conv. renewables		1657	10.9%	829	7.5%	8800	3294
All renewables		7675	50.7%	3618	32.6%	19,800	8425

technologies other than large hydro-reservoirs and run-of-the-river with installed capacity larger than 40 MW).[10] Secondly, the Chilean policy on renewable generation is in line with several other countries that have renewable policy targets to meet by 2020, 2025 and/or 2030 (including the EU, China, India, Russia, Brazil, Australia and Canada, among others).[11] Thirdly, a period of 10 years is a reasonable time period during which to have the flexibility to build any generating plant, some of which will need several feasibility analyses, environmental impact studies, environmental permissions, and time for their construction itself.[12]

In terms of the risk of the generating system, we use a $CVaR_{\alpha=5\%}$ capturing the expected costs of total energy production in the worst 5% of cases (i.e. in the 5% of cases with the highest generation costs). In expansion planning for the Chilean CIS, we consider the possibility of expanding plants' capacity based on (i) technologies already in use in the Chilean power system, and (ii) new technologies that may be developed. The energy generating system in Chile (as of December 2014) is composed of conventional renewable technologies (hydro-reservoirs and run-of-the-river), non-conventional renewables (small hydro, solar PV, wind and biomass) and fossil fuel technologies (oil, liquefied natural gas (LNG) and coal). Given that the model takes into account the use of new technologies, we also include the use of other non-conventional renewables such as geothermal energy and concentrated solar power (CSP).

Table 1 displays the installed capacity by the starting point at 2014, average capacity factors (see Section 3.3), and projected upper bounds in terms of future new power capacity per power-generating technology. The installed capacities as of 2014 are taken from the Chilean Association of Electricity Generators (2014). The average capacity factors are obtained from the Chilean Ministry of Energy, with measures calculated by the Department of Geophysics at the University of Chile. The upper-bound capacities reflect the maximum capacities that could be installed by 2025 based on Chile's energy resources and geographical conditions, the potential generation developments as analyzed by the Chilean Ministry of Energy, and transmission lines in the areas where developments could potentially happen.

This table also reports the 'effective' installed capacity by 2014, which is the installed capacity by 2014 (Column 2) multiplied by the capacity factor (Column 1) for each generating technology. The 'effective' capacity is also reported for the projected upper bounds per power-generating technology. Additionally, this table presents the installed capacity as a proportion of the total installed capacity in the Chilean CIS.

Table 1 reveals that a large proportion of the Chilean CIS' installed capacity was comprised of renewable generation by 2014; namely, 50.7% of the installed capacity by 2014 was based on renewable technologies, and this represented 32.6% of the 'effective' installed capacity. This is important, as renewable generation is intermittent. In contrast, plants generating fossil fuels do not experience intermittency issues as commonly observed in plants based on renewables. Similar to Inzunza et al. (2016), we assume that the fossil fuel technologies exhibit a constant capacity factor of 100%. However, in unreported results, we modify the capacity factor to a stable 85% and discover the results do not qualitatively change from those presented here.

In the implementation of the model, we also include the risk associated with the generation intermittency of renewable technologies, which induces penalties due to energy supply interruptions (see Eq. (1)). The penalty used in our model in the

[10] Large hydropower plants (hydro-reservoirs and run-of-the-river) are considered 'conventional' renewable energy sources (Chilean Non-Conventional Renewable Energy Law #20.257).

[11] See Renewables 2015 Global Status Report, from REN 21.

[12] For instance, the International Energy Agency reports that, for a large hydro-reservoir plant, it can take up to 7.5 years for the construction alone, which only starts following studies of feasibility, studies of environmental impact, and once environmental permissions are in place.

Table 2
Investment costs, maintenance costs and emission factors.
Maintenance costs do not include fuel costs. Solar PV is solar photovoltaic technology, while solar CSP is concentrated solar power. The fuel costs of the coal, liquefied natural gas (LNG) and oil technologies are described in Table 3. The fuel cost in the case of biomass generation is that used in the Integrated Biomass Gasification Combined Cycle (IBGCC) technology, of US$15.5 per MWh, which is based on projections described in the report "Energy Scenarios Chile 2030" and assumed to be constant.

	Annuitized investment cost [$/kW-year]	Maintenance cost [$/MWh]	CO_2 equivalent (CO_2e) emission factor [TCO_2e/GWh]
Coal	221,000	5	949
Oil	55,000	15	779
Hydro	202,000	5	7
Wind	188,000	9	11
Solar PV	132,000	4	48
Liq. Nat. Gas (LNG)	93,000	3	436
Run-of-river	202,000	5	4
Biomass	241,000	4	24
Geothermal	395,000	13	28
Small hydro	303,000	7	4
Solar CSP	463,000	8	20

Table 3
Fossil fuel prices and correlations.

	Coal	LNG	Oil
Mean returns	2%	2%	6%
Standard deviation returns	12%	14%	21%
Expected price (2025) [$/MWh]	43	107	204
	Correlation coefficients		
Coal	1	–	–
LNG	0.4	1	–
Oil	0.2	0.7	1

case of unsatisfied demand is US$400 per MWh of unmet demand. This value is established by Article 19 of Decree 26 of the Chilean Law of Electricity Service #21194, which specifies a penalty of 209 Chilean Pesos per kilowatt-hour not covered (which is equivalent to US$400 per MWh, based on the exchange rate in 2014).

Table 2 reports investment costs, maintenance costs, and carbon dioxide equivalent (CO_2e) emission factors. The investment costs and maintenance costs are obtained from projections described in a report entitled "Escenarios Energéticos—Chile 2030".[13] Investment costs are annualized by considering the generating plant's lifespan, and maintenance costs do not include fossil fuel costs. The CO_2e emission factors are also obtained from the same report.

This table indicates that fossil fuel generation is generally less expensive than other forms of generation in terms of investment costs. For instance, generation based on oil technology has the lowest annuitized investment costs, while gas-based generation has the lowest maintenance costs. However, fossil fuel generation has the highest levels of CO_2e emissions.

In implementing the model, we assume that the stochastic economic variables are fossil fuel prices and the energy demand. However, other economic factors' variability could be included in other implementations. Thus, we will first explain how we model the evolution of fossil fuel prices; at the end of this section, we will then describe how we include the variability in energy demand.

Fossil fuel generation includes an economic risk associated with the volatility of fossil fuel prices, which can have an important impact on the risk exposure of operational costs. Thus, in the implementation of the model in the Chilean CIS, we assume that fossil fuel price returns are stochastic and follow multivariate geometric Brownian motion. The parameters of these stochastic processes (i.e. mean returns, standard deviations and correlations) are calculated using historical fossil fuel prices between 1984 and 2014, obtained from the Energy Information Administration (U.S. Department of Energy), and are reported in Table 3.

We characterize the stochastic intermittency of renewable generation in the Monte Carlo simulations of the slave problem in Benders' decomposition. In the case of solar and wind generation, as a first step, we obtain data for the year 2014 on hourly profiles for solar radiation and wind power in different regions of Chile, provided by the Department of Geophysics at the University of Chile, which has monitoring stations across the country recording solar and wind conditions. In addition, we obtain hourly hydrological data, also for the year 2014, for each river in which there is a run-of-the-river plant (from the National Commission of Energy). Then, we calculate the capacity factors, hour-by-hour, using the data on weather and

[13] "Escenarios Energéticos—Chile 2030 was developed by a group of Chilean institutions related to the electricity-generating sector. The advisory committee included participants from the Chilean Ministry of Energy and the Chilean Ministry of Environmental Affairs, and academics from the Universidad de Chile and Pontificia Universidad Católica de Chile, among other non-profit organizations.

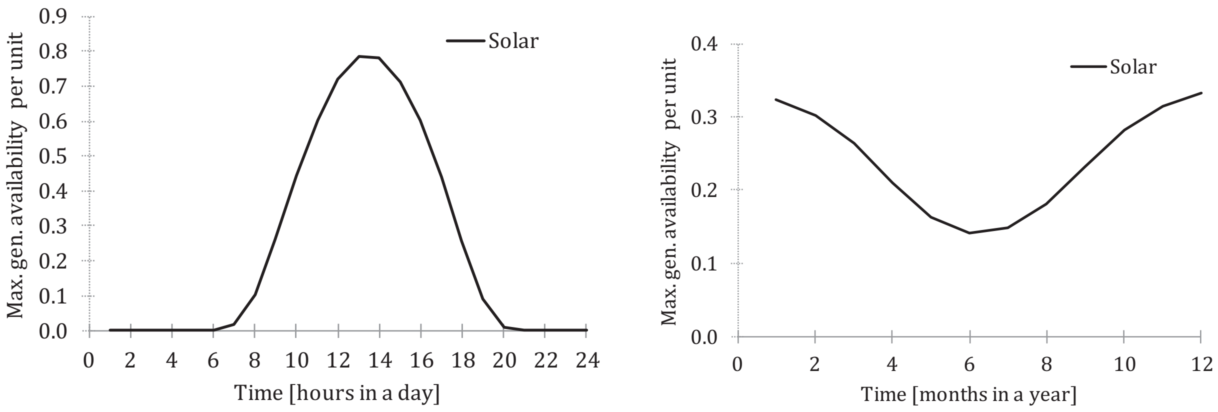

Fig. 1. Average solar profile in terms of maximum generation availability in each hour of a day and in each month of 2014.

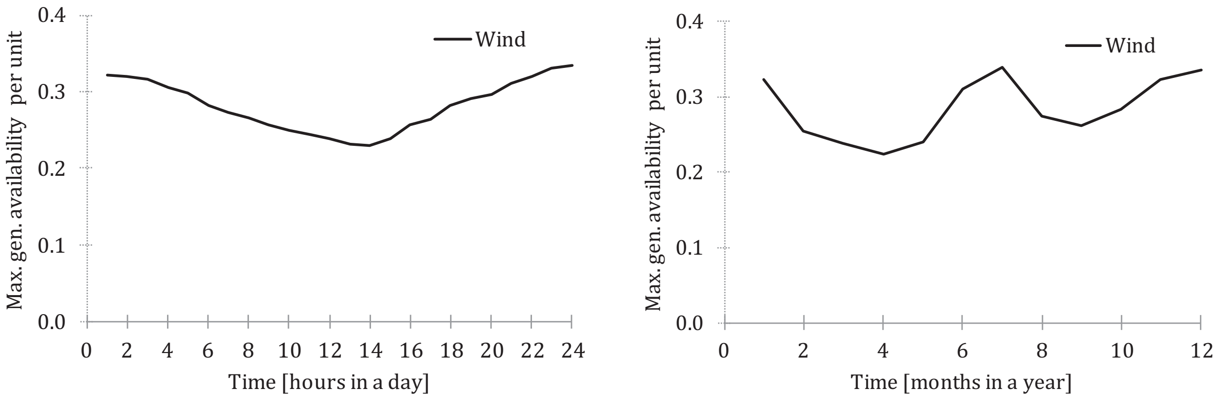

Fig. 2. Average wind profile in terms of maximum generation availability in each hour of a day and in each month of 2014.

Table 4
Probability distribution of capacity factors observed in historical hydrological data.

# of scenario	1	2	3	4	5	6	7	8	9	10
Probability [p.u.]	0.06	0.06	0.13	0.17	0.13	0.11	0.17	0.08	0.04	0.06
Reservoir average capacity factor	16%	24%	30%	34%	41%	46%	52%	57%	63%	71%
Run-of-river average capacity factor	42%	49%	51%	47%	51%	53%	55%	58%	54%	59%

hydrological conditions, based on the efficiency with which the generating plants transform solar radiation, wind power and hydropower into electricity. In the case of hydropower, we improve on the historical simulations, since we also obtain average historical hydrological data over the last 50 years for each river in which there is a run-of-the-river plant. This allows us to change the level of the hydrological conditions, and thus capture the effect of dry, medium and wet years in the historical simulations.

Fig. 1 reports the solar generation profile on an average day and in each month of 2014. The data reveals that the hours of 12:00 to 14:00 exhibit the highest solar generation, while the months of December, January, and February are the highest due to the southern hemisphere's summer season. Fig. 2 presents the wind generation profile for an average day and in each month of the year; wind generation reaches its highest levels at night and in January, July, and December.

Fig. 3 shows, for small hydro generation, the maximum generation availability on an hourly basis over an average day, and in each month of the year. The average behavior of small hydro generation reflects the fact that, in Chile, a significant proportion of rivers receive snowmelt water. Thus, the generation availability increases progressively during the day, when snow is melted by the sun, and is also at its highest during the Chilean summertime (December and January). In addition, Table 4 presents summary statistics for the probability distributions of the average capacity factors of run-of-the-river and hydro-reservoir plants, based on historical hydrological data.

We use a simple methodology for our Monte Carlo simulations for solar, wind, and hydropower generation. As a first step, we divide the year 2014 into four seasons: December through February, March through May, June through August, and September through November. We then generate each simulated day by randomly selecting a day from the corresponding

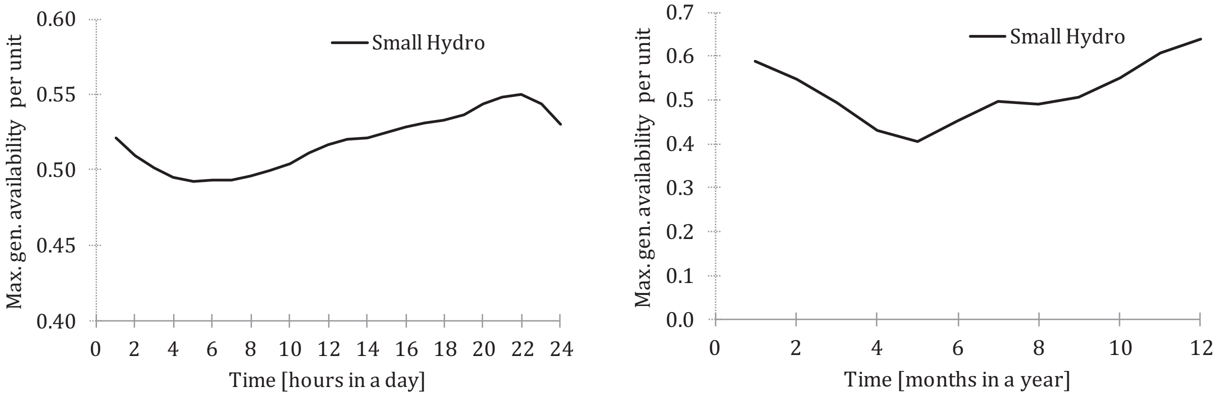

Fig. 3. Average small hydro generation profile in terms of maximum generation availability in each hour of a day and in each month of 2014.

season in the year 2014. The simulation incorporates these randomly selected days to provide the *hourly conditions*. We repeat the same procedure several times for each day and each simulation to characterize each *hour* of each year τ.[14] This is a straightforward approach given the available historical data.[15]

We assume that biomass generation and geothermal generation exhibit a constant capacity factor of 85%, which is based on the “Escenarios Energéticos—Chile 2030” report. This assumption parallels previous studies, which indicate that both technologies provide important benefits in their reliable, stable energy production compared to other renewable resources, such as solar and wind power (e.g., Perez-Navarro et al., 2010; Heydari and Askarzadeh, 2016; Kulasekara and Seynulabdeen, 2019). Moreover, we assume that the fuel costs for biomass generation are those used in Integrated Biomass Gasification Combined Cycle (IBGCC) technology of US$15.50 per MWh, which is based on projections described in the “Escenarios Energéticos—Chile 2030” report and assumed to be constant.

We generate Monte Carlo simulations for electricity demand in a manner similar to how we produced the capacity factors for the solar, wind, and hydropower technologies, in that we use a year divided into seasons. We obtain the 2014 demand profile at hourly intervals from the Chilean National Commission of Energy, an institution associated with the Chilean Ministry of Energy. After dividing the year 2014 into four seasons, we adjust the demand profile based on the 2025 projections from the Chilean Ministry of Energy, which consider economic growth and population levels, among other variables.[16] In a given simulation, we randomly select a day from a season in 2014; this day is used to provide the hourly conditions representing a full day in the respective season. We replicate this process for electricity demand on each day of each season in each simulation.

It is important to note that when selecting *one day* to generate capacity factors for the solar, wind, and hydropower technologies, we select the *same day* to simulate electricity demand. Therefore, the same day is used to produce all features for one simulated day, which allows us to consider the potential *correlation* among the simulated variables; for example, we want to consider that on cloudy days in Chile, there is generally a higher chance of having high levels of wind.

Fig. 4 presents the average electricity demand profile for an average day and in each month of the year. This indicates that high electricity demand occurs between 12:00 and 14:00, which corresponds to the highest availability of solar generation (Fig. 1). Further, demand is also high at around 22:00, which corresponds to the highest generation availability of both wind (Fig. 2) and small hydro-power (Fig. 3).

In terms of the months of the year, demand is high in July, when there are high levels of wind generation (Fig. 2), and December, when there is greater availability from solar, wind, and small hydro-power, (Figs. 1 to 3, respectively). Therefore, renewables can provide these basic diversification benefits, relative to not only a decrease in the exposure to changes in fossil fuel prices, but also the interaction between renewable generation availability and electricity demand. These basic diversification benefits could also appear in other countries or regions, albeit in different forms depending on geographical characteristics. The Supplementary Appendix A reports additional parameters used in the model's implementation.

[14] It is important to note that due to hydro-reservoirs' buffering feature, it is not reasonable to calculate their hourly capacity factor as we do for the run-of-the-river and small hydro-power technologies. Therefore, we assume that water inflows are constant each week, and we calculate a weekly capacity factor using the hydro-reservoir plants' efficiency in producing electricity.

[15] The implementation described in this section is only an example of the model's use; thus, other simulation approaches could be used in the case of long historical profile time-series for generating solar, wind, and hydropower.

[16] The Chilean Ministry of Energy's projections use a 5% demand growth rate (on an annual basis). In unreported results, we perform analyses using growth rates of 3% and 7% to discover they deliver qualitatively similar results to those presented here.

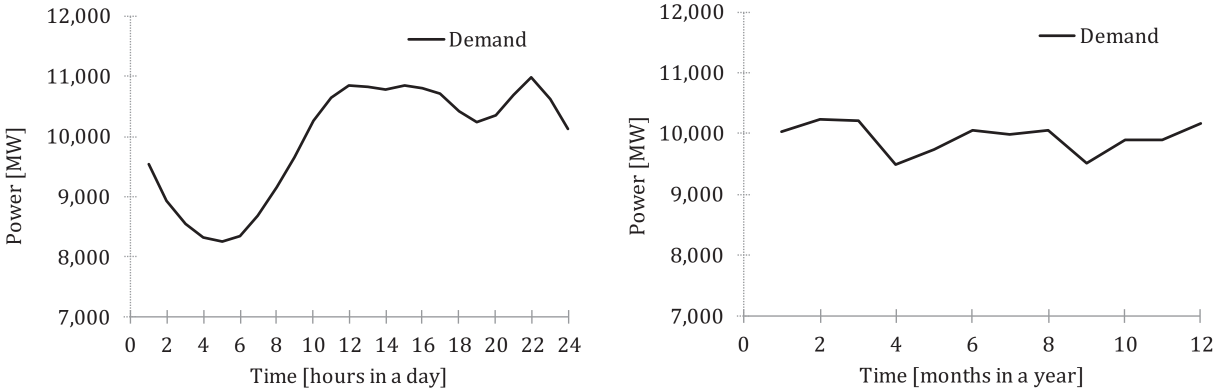

Fig. 4. Average demand profile of electricity consumption in each hour of a day and in each month of 2014.

5. Results of model's implementation

5.1. Benchmark case: optimal electricity generation planning without environmental policies

This section presents the results from the model's implementation; however, we first consider optimal generation planning without any environmental policy, or $EP(s) = 0$ in Eq. (2) for all economic states. This initial analysis aims to obtain a benchmark against which to compare optimal generation planning under policies related to renewable generation (see Sections 5.2 and 5.3).

Each panel in Table 5 displays the results for *three* optimal expansion planning setups in the year 2025, which exhibit diverse levels of risk. In this table, the level of risk—as defined by the *CVaR*—increases from left to right. The extremes in this table are on the left-hand side, in which we present the optimal generation portfolio with the minimum risk and maximum cost; and on the right-hand side, in which we show the optimal generation portfolio with the minimum cost and maximum *CVaR*.

Panel A incorporates a penalty for the *lost load* of US$400 per MWh of unsatisfied demand, as explained in Section 4; this is the real value established by the Chilean Law of Electricity Service (see Article 19 of Decree 26 of the Chilean Law of Electricity Service #21194). Panel B incorporates a penalty of US$100 per MWh of unsatisfied demand to analyze the impact of a hypothetical, different penalty for unmet electricity demand, which could be the case for investors in other countries.

In each of the three optimal expansion planning setups (in Panels A and B), we present different characteristics of the optimal generation portfolios. First, we report the *new* generating capacity installed by 2025 for each generating technology, which is added to the installed (already built) capacity in 2014. Second, we report the average percentage of the capacity *newly* installed by 2025, which will be used as reserves to address intermittent generation issues (see Section 3.5). Third, we present the total capacity installed per generating technology by 2025, which is the generating capacity already installed in 2014 (see the second column of Table 1), plus the *new* generating capacity installed by 2025 (see, e.g., the first column in Table 5 for the first optimal expansion planning setup). Fourth, and similar to Table 1, we report the average *effective* total capacity installed by 2025, which is the total capacity installed by 2025 (see, e.g., the third column of Table 5 for the first optimal expansion planning setup), multiplied by the capacity factor for each generating technology (see the first column of Table 1). Fifth, we illustrate the average generation per hour for each of the generating technologies by 2025. Sixth, we report the percentage of generation covered per generating technology by 2025.

We also report the percentage of demand not covered, or the *lost load* in Eq. (1). To measure the optimal generation portfolios' levels of diversification, we use the Herfindahl–Hirschman Index (HHI) of the capacity installed for and energy generated by the different generating technologies by 2025. The HHI measures the concentration of installed capacity and energy generation, ranging from zero to one. Diversification is then measured as one minus the HHI of the installed capacity, *Diversific.*(*total cap*), and energy generated, *Diversific.*(*total gen*), for the different power technologies, with higher levels of diversification indicated by higher values. Specifically, we compute the diversification measures as follows:

$$Diversific.(total\ cap) = 1 - \sum_{i \in I} (pcap_i)^2 \tag{28a}$$

$$Diversific.(total\ gen) = 1 - \sum_{i \in I} (pgen_i)^2 \tag{28b}$$

where $pcap_i$ and $pgen_i$ are the proportions of installed capacity and energy generated by generating technology i, respectively. Moreover, both panels in this table report the CO_2e emissions (expressed in millions of tons of CO_2e), the total expected cost (*Exp. Cost*), and the energy production *CVaR* for each optimal expansion planning setup.

Table 5
Optimal expansion planning without an environmental policy.
This table shows three optimal expansion planning setups constrained by different levels of risk in terms of *CVaR*. Risk increases as we move from left to right. Solar PV and solar CSP were defined in Table 1. Panels A and B show results for different penalties imposed for unmet energy demand.

	Optimal expansion planning setups constrained by different levels of risk in terms of CVaR																	
	Portfolio under minimum CVaR and maximum cost						Portfolio under intermediate CVaR and intermediate cost						Portfolio under maximum CVaR and minimum cost					
	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.
	Panel A: Opt. portfolios without environmental policies and a penalty for lost load of 400 USD/MWh																	
Coal	2050	89.1%	4444	4444	2618	26.3%	1626	60.2%	4020	4020	3041	30.6%	1335	60.6%	3729	3729	2920	29.4%
Oil	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	46	0.5%
Hydro	262	0.0%	4315	1888	1888	19.0%	2440	2.0%	6493	2841	2819	28.4%	2947	1.8%	7000	3063	3040	30.6%
Wind	3366	0.0%	4000	1126	1126	11.3%	0	0.0%	634	179	179	1.8%	0	0.0%	634	179	179	1.8%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	69	0.7%	0	0.0%	2777	2777	188	1.9%	0	0.0%	2777	2777	276	2.8%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	0.0%	1000	850	850	8.6%	0	0.0%	504	428	428	4.3%	0	0.0%	504	428	428	4.3%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	0	0.0%	350	181	181	1.8%
Solar CSP	200	0.0%	200	104	104	1.0%	0	0.0%	0	0	0	0.0%	0	0.0%	0	0	0	0.0%
Lost load						0.0%						0.0%						0.0%
Non-conv. renewables	7143	0.0%	8800	3294	3294	33.1%	3081	0.0%	4738	1821	1821	18.3%	2631	0.0%	4288	1588	1588	16.0%
All renewables	9440	0.0%	17115	7251	7250	73.0%	7556	0.0%	15231	6730	6708	67.5%	7613	0.0%	15288	6719	6696	67.4%
Fossil fuel + renewables	11490	15.9%	26639	16,774	9938	100.0%	9182	11.2%	24331	15830	9938	100.0%	8948	9.6%	24097	15,528	9938	100.0%
Diversific. (total cap)				0.87						0.84						0.83		
Diversific. (total gen)				0.82						0.77						0.77		
MM tons CO_2e				22.84						26.68						26.32		
Exp. Cost [MM $]				6571						6172						6150		
CVaR [MM $]				7746						8202						8473		
	Panel B: Opt. portfolios without environmental policies and a penalty for lost load of 100 USD/MWh																	
Coal	1222	44.9%	3616	3616	3068	30.9%	1161	17.1%	3555	3555	3356	33.8%	832	46.5%	3226	3226	2839	28.6%
Oil	0	0.0%	2303	2303	2	0.0%	0	0.0%	2303	2303	13	0.1%	0	0.0%	2303	2303	15	0.2%
Hydro	0	0.0%	4053	1773	1759	17.7%	509	5.8%	4562	1996	1983	20.0%	2947	1.8%	7000	3063	3040	30.6%
Wind	3366	0.0%	4000	1126	1126	11.3%	67	0.0%	701	197	197	2.0%	0	0.0%	634	179	179	1.8%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	41	0.4%	0	0.0%	2777	2777	180	1.8%	0	0.0%	2777	2777	215	2.2%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	66.7%	1000	850	569	5.7%	496	32.0%	1000	850	715	7.2%	0	0.0%	504	428	331	3.3%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	0	0.0%	350	181	181	1.8%
Solar CSP	93	0.0%	93	49	49	0.5%	0	0.0%	0	0	0	0.0%	0	0.0%	0	0	0	0.0%
Lost load						0.4%						2.1%						2.7%
Non-conv. renewables	7036	4.7%	8693	3239	2958	29.8%	3644	4.4%	5301	2261	2126	21.4%	2631	0.0%	4288	1588	1491	15.0%
All renewables	9071	3.6%	16746	7080	6785	68.3%	6188	3.0%	13863	6325	6178	62.2%	7613	0.7%	15288	6719	6599	66.4%
Fossil fuel + renewables	10293	8.5%	25442	15,776	9895	99.6%	7349	5.3%	22498	14960	9727	97.9%	8445	5.2%	23594	15,025	9668	97.3%
Diversific. (total cap)				0.87						0.86						0.83		
Diversific. (total gen)				0.81						0.79						0.77		
MM tons CO_2e				26.41						29.37						25.19		
Exp. Cost [MM $]				6384						6107						6068		
CVaR [MM $]				7625						7801						7902		

It is noteworthy that the average generation values (the fifth column for the first optimal expansion planning setup) are not necessarily the same as the installed capacity per hour by 2025 (for example, as in the third column for the first optimal expansion planning setup) for the different generating technologies. This is because, as explained in Section 3.5, the installed capacity per hour does not indicate that a given generating technology can produce at 100% of its potential production due to capacity factors (see the first column of Table 1). Actually, it is more appropriate to compare the average generation per hour for each technology and the average *effective* total capacity installed (e.g. the fourth column for the first optimal expansion planning setup), in which the latter is the total capacity installed multiplied by the respective capacity factors.

As explained at the beginning of this section, we report three optimal expansion portfolios in which the level of risk as defined by the *CVaR* increases as we move from the left- to the right-hand side of the table. A basic diversification benefit explains the lower levels of risk among the optimal portfolios on the left-hand side. For example, Panel A reveals that the portfolio with a minimum *CVaR* has a $Diversific.(total\ cap) = 0.87$ and $Diversific.(total\ gen) = 0.82$, while the portfolio with a minimum cost in the same panel has a $Diversific.(total\ cap) = 0.83$ and $Diversific.(total\ gen) = 0.77$.

The level of diversification in the generation portfolios with lower risk increases through an increase in *new forms* of energy generation, such as energy production based on 'non-conventional' renewable technologies.[17] For instance, Panel A indicates that the non-conventional renewable generation in the generation portfolio with a minimum *CVaR* contributes 33.1% of the total generation, while 16.0% of generation in the optimal portfolio with minimum cost comes from non-conventional renewables. Regarding the optimal planning with minimum *CVaR* as noted in Panel A, newly installed capacity and generation occurs in technologies based on wind, solar PV, biomass, geothermal, small hydro-power, and CSP. The simultaneous use of *diverse* non-conventional renewable generation decreases risk due to the basic diversification benefits in the generation portfolio, as can be observed on the left-hand side of the table. For instance, Section 4 noted that despite small hydro-generation having, on average, the lowest production between 04:00 and 05:00 (see Fig. 3), at that time there is high generation availability from wind (see Fig. 2) and the energy demand is also low (see Fig. 4).

This table also reports that the newly installed capacity and generation from hydro-reservoir technology reach their lowest levels under optimal planning with minimum *CVaR*, which is unexpected. Although hydro-reservoir generation is convenient—given its relatively low investment and maintenance costs, and therefore, its appeal in expansion planning—it also produces a high risk of exposure due to potentially poor hydro-power conditions in worst-case scenarios. For instance, hydro-reservoir plants produce electricity with a capacity factor of only 16% in very dry years (see Table 4), which is difficult to hedge. It is also noteworthy that hydro-reservoir generation is replaced by additional, diverse, and non-conventional renewable technologies. This is because each non-conventional renewable-generating technology can be used to *hedge* the risks of the other technologies used for energy production, as previously described.

Panel A demonstrates that no unmet energy demand (lost load) exists in the three optimal portfolios when a penalty occurs for unsatisfied energy demand of US$400 per MWh. This is because the Chilean penalty of US$400 per MWh for unmet energy demand as established by the Chilean Law of Electricity Service is higher than: (i) the cost of producing electricity with some unused technology capacity; and (ii) the cost of building additional generation reserves, such as (i.e. extra generating capacity used as backup, as explained in Section 3.5), which can be used to reduce periods of unsatisfied demand due to the intermittent energy production from renewable-generating technologies.

This table shows that the model selects reserves that are mainly based on coal technology. In fact, we can observe that, in all optimal portfolios in both panels, the model decides to install *new* capacity for coal power, but the average use of the *effective* capacity of coal is lower than 100%.[18] When *new* generating capacity from coal is installed, part of the new generating capacity is used as reserves to deal with the generation intermittency issues (see the second column for all optimal portfolios). Coal generation is used for reserves because (i) it is very stable in terms of the energy generated (i.e. it has a high average capacity factor, see Table 1), (ii) it has, on average, a lower fossil fuel price than other stable technologies such as oil and gas generation and (iii) it has the lowest price volatility of the fossil fuel technologies.

Thus, in the portfolios with the lowest level of risk, when the generation from non-conventional renewable technologies (which is in general intermittent) increases, we observe a greater *newly* installed coal generation capacity, which is partially used for reserves. For instance, Panel A shows that the portfolio with minimum *CVaR* has a newly installed coal generation capacity of 2050 MWh (and 89.1% of this capacity is used for reserves), while the portfolio with minimum cost has a newly installed coal generation capacity of 1335 MWh (and 60.6% of this capacity is used for reserves).

Nevertheless, in the hypothetical case that the Chilean penalty decreased from US$400/MWh as in Panel A to US$100/MWh as in Panel B, we observe that the lost load can reach a level of 0.4% (2.7%) in the generation portfolio with minimum risk (cost). This happens, for example, in some states of the economy in which the generation costs of some technologies (e.g. the fuel price of coal generation) increase until they exceed the penalty for unmet demand (i.e. the generation cost is higher than US$100/MWh). In fact, the *newly* installed coal generation capacity—which is used as backup energy—decreases in all optimal portfolios when moving from Panel A to B. For instance, in the optimal portfolios with minimum

[17] As explained in Section 4, Chilean law defines 'non-conventional' renewable technologies as all renewable technologies other than large hydro-reservoirs and run-of-the-river systems with an installed capacity greater than 40 MW (Chilean Non-Conventional Renewable Energy Law #20.257).

[18] The average use of the *effective* total capacity installed by 2025 is the average generation per hour (see, e.g., the fifth column of Table 5 for the first optimal expansion planning setup) divided by the average *effective* total capacity installed (see, e.g., the fourth column of Table 5 for the first optimal expansion planning setup) in 2025 for each generating technology

CVaR, the *newly* installed generation capacity based on the coal technology is 2050 MWh in Panel A, but just 1222 MWh in Panel B.

It is important to note that a lost load of 0.4% (2.7%) is large, being equivalent to 1.5 (9.9) days of the year without any electricity in Chile. This level of insufficiency of electricity supply could induce an enormous negative impact on the economic performance of the country. For instance, insufficient electricity generation can generate massive problems in health and education services, industrial production, consumption, telecommunications, exchange of goods, financial systems and security structures, amongst other things.

It is also noteworthy that in the case of minimum risk, Panel A exhibits a lower level of CO_2e emissions (22.84 million tons of CO_2e) than Panel B (26.41 million tons of CO_2e), but Panel A has a higher total installed capacity for coal technology (4444 MWh) than Panel B (3068 MWh). This is explained by the fact that the model changes the use of coal-generating technology. In Panel A, the model installs new coal capacity mainly for use as generation reserves, while in Panel B the model installs new coal capacity for actual generation. In Panels A and B, 89.1% and 44.9% of the new coal capacity is used for reserves, respectively. Thus, the average generation based on the coal technology in Panel A (2618 MWh) is lower than that in Panel B (3616 MWh), which induces a lower level of CO_2e emissions in Panel A compared with Panel B.

We can observe that the portfolios with a lower level of *CVaR* are more expensive. This is because the diversification of these portfolios implies additional costs: the higher costs of non-conventional renewable generation and the cost of installing extra capacity for coal generation to be used as generation reserves. For that reason, for example in Panel A, the expected cost of the generation portfolio with minimum *CVaR* is the largest amongst all the planning setups, with a value of $Exp.\,Costs\ [MM\ \$] = 6571$.

Most importantly, it is relevant to note that despite its higher expected cost, the generation portfolio with a minimum *CVaR* still provides an optimal economic point from a risk-reduction perspective. This is a key result because a significant level of non-conventional renewable technology can be economically justified if reducing the generating system's risk is more important than reducing costs. For instance, if a risk-reduction perspective is followed, the Chilean policy target of 20% of generation from non-conventional renewable technologies can be reached without any environmental policy.

Further, some technologies are too expensive to be used, despite having already been installed by 2014. In the model, we set as a starting point the installed capacities as of 2014 for all technologies. However, this assumption does not ensure that the model will decide to generate electricity with that installed capacity. For instance, the oil and LNG technologies do not have their installed capacities expanded from the initial setup in 2014 (see the first column in all optimal portfolios) in any of the optimal expansion planning setups. The oil and LNG technologies are not activated in terms of *new* capacity, as they are not economically viable. Both technologies are highly expensive in terms of fossil fuel prices (see Table 3). Furthermore, despite the fact that there is already some installed oil technology capacity, this installed capacity is barely used for generation. Only in the case of optimal planning with a minimum level of costs (on the right-hand side of the table), is there a small amount of generation through oil power.

It is important to mention that, for the capacities of all technologies installed by 2025, even that part already built by 2014, an *annuitized* investment cost has to be paid (see Eq. (2)). This implies two important features of the model. Firstly, it is costly to have oversized generating plants.[19] Thus, oversized *newly* installed capacity is only observed if that capacity is used for generation reserves (e.g. in our model implementation, this is the case for the *newly* installed coal capacity used for generation reserves, as explained above). Secondly, for the technologies not used in 2025 despite already having been installed in 2014 (e.g. the oil technology), the *annuitized* investment cost is still paid. This is an important point since, for example in the case of the oil technology, it is preferable to install and use new and cheaper technologies (in terms of the combination of investment and operational costs) than to generate electricity using the already installed capacity of the oil-based plants.

As previously explained, we observe on the right-hand side of the table that cost reductions are obtained at the expense of an increase in the level of risk. However, despite the use of the *CVaR* as a measure of risk having important benefits (see Section 3.1), the *CVaR* is a risk measure that is affected by the *level* of the expected cost of the system. This is because, as we explained in Eq. (4), the $CVaR_\alpha$ captures the expected cost of total energy production in the worst α% of cases.[20] Thus, suppose that there are two energy systems (e.g. from two different private investors) with the same *shape* of distribution of potential costs from different states of the economy. Then, one of these energy systems should have a higher level of *CVaR* than the other, if the former has a higher expected cost than the latter. Hence, it is better to evaluate the following ratio: $(CVaR - Exp.\ Cost)/Exp.\ Cost$. This ratio reflects the *CVaR* of each expansion planning setup, adjusted by the level of expected cost of the system. Consequently, in the example with two energy systems described above, the ratio $(CVaR - Exp.\ Cost)/Exp.\ Cost$ will give the same value in each case.

Thus, to assess potential risk changes, we evaluate the ratio $(CVaR - Exp.\ Cost)/Exp.\ Cost$, since each generation portfolio has different expected costs. For example, this ratio in the portfolio on the left-hand (right-hand) side is 0.179 (0.378). Thus, the level of risk reaches the highest values in the case of optimal planning with minimum cost. The increase in the level of

[19] Although in our model it is costly to have oversized generating plants due to the annuitized investment cost, we do not consider the environmental costs related to oversized generating units in terms of the damage that such plants can cause to the wildlife around them. This is because we are modeling the costs to a private investor, who does not *necessarily* consider environmental damages in her/his optimal decisions.

[20] In the model implementation, we consider the expected value in the 5% of scenarios with the highest generation costs in calculating the *CVaR*, as described in Section 4.

risk is due to three elements. First, there is a reduction in the generation reserves used as backup for potential generation intermittency. Second, there is an increase in the newly installed capacity and generation of the hydro-reservoir technology. As previously explained, despite the hydro-reservoir technology having relatively low investment and maintenance costs, it also has high risk levels of non-generation in very dry years. Third, there is a reduction in the levels of diversification coming from *new forms* of generating technologies, as the non-conventional renewable generation is reduced.

Nevertheless, generation by some non-conventional renewable technologies is still triggered in the case of optimal planning with minimum cost: the solar PV and geothermal technologies. The newly installed capacity of solar PV is mainly due to its lower maintenance costs, relatively low investment costs (in relation to other non-conventional renewable technologies) and the favorable climatic conditions in Chile, where there is a high percentage of sunny days. Geothermal technology is also convenient, since it has a high capacity factor due to the geographical location of Chile (close to volcanoes in the Andean Mountains).

5.2. Environmental policy's effects on reaching a renewable policy target

In this section, we show the same generation allocation analysis as in Table 5, but now we impose an environmental policy regarding the achievement of a minimum level of renewable electricity generation by 2025. We impose that a minimum of 20% of the electricity demand should be satisfied through *non-conventional* renewable technologies, by means of a strong *one-off penalty* to be applied if the target is not reached at the end of each year (see Eq. (17)). Here, K is the penalty applied if a minimum level of demand is not supplied by non-conventional renewable electricity generation in the target year, where $i^{NCR} \in \{1, 2, \dots, I^{NCR}\}$ is an indicator for non-conventional renewable technologies, with $I^{NCR} \leq I$ and $Target^R = 0.2$. We set K large enough that the renewable policy target is reached in all states of the economy. This analysis is presented in Table 6.

This table demonstrates that the environmental policy does not affect the generation portfolios with minimum levels of *CVaR*. If we compare Tables 5 and 6, we can observe that the optimal planning setups on the left-hand side are the same in both tables, as these generation portfolios already met the 20% non-conventional renewable generation target without penalty. Nevertheless, Table 6 reports that the policy target constraint is active when planning decisions focus more on reducing costs than risk.

The optimal planning setup with minimum cost (right-hand side of Tables 5 and 6) reveals that when the environmental policy is imposed, small hydro-power and biomass generation are preferred for reaching Chile's renewable goal by 2025. For instance, in Panel A under the optimal portfolio with minimum cost, the newly installed capacity for small hydro-power increases from 0.0 MWh in Table 5 to 450 MWh in Table 6; meanwhile, the newly installed capacity for biomass expands from 0.0 MWh in Table 5 to 196 MWh in Table 6.

The small hydro and biomass technologies are triggered because they are characterized by a combination of relatively high average capacity factors and relatively low investment and operational costs compared to other non-conventional renewable technologies (see Table 1). This analysis is useful in showing that there is no optimal, single technology to use for electricity generation under environmental policies. The increase in electricity generation from these two non-conventional renewable generating technologies also induces an increase in coal's installed capacity. This is because, as described in Section 5.1, coal power is used for generation reserves to deal with the intermittency of the additional renewable generation.

Naturally, the optimal portfolios with minimum cost in Table 6 are more expensive than the same portfolios in Table 5. For example, in Panel A of these tables, the expected costs of these portfolios are US$6,150 million in Table 5 and US$6208 million in Table 6. This is to be expected since the model optimization has an additional constraint that a minimum of 20% of the electricity demand should be satisfied through non-conventional renewable technologies, which induces further costs: (i) higher costs of the new non-conventional renewable generation (in this case, small hydro and biomass); and (ii) the additional installed capacity for generation reserves used as backup to reduce the intermittency risk of the newly installed capacity of renewable technologies (which are also costly).

Moreover, since the installed capacity and generation of plants based on small hydro and biomass have been augmented, the diversification level of the system also rises. For instance, the optimal portfolio with minimum cost in Table 5 Panel A has $Diversific.(total\ cap) = 0.83$ and $Diversific.(total\ gen) = 0.77$, which increase in Table 6 Panel A to 0.84 and 0.78, respectively.

One may posit that the differences between Tables 5 and 6 are minor. For instance, the right-hand side of Panel A displays only a 0.9% (6208/6150 − 1) increase in expected costs, while $Diversific.(total\ cap)$ and $Diversific.(total\ gen)$ increase by 1.2% (0.84 / 0.83 − 1) and 1.3% (0.78 / 0.77 − 1), respectively. However, these small changes induce much larger economic benefits due to the decrease in risk. As explained in Section 5.1, to analyze the risk reductions in Table 6 relative to Table 5, it is better to compute the ratio $(CVaR - Exp.\ Cost)/Exp.\ Cost$, which is the *CVaR* adjusted by the system's expected cost. This ratios on the right-hand side of Panel A in Tables 5 and 6 are 0.378 and 0.303, respectively, which represent a decreased risk of 19.8% from Tables 5 to 6. Consequently, the level of risk involved in producing the energy is reduced when the environmental policy is imposed, due to the increase in the diversification of the power system. This means that environmental policies can be justified, not only based on the benefits to the environment, but also economically, from the perspective of a risk reduction, using basic diversification gains.

Table 6
Optimal expansion planning under an environmental policy in which a strong penalty is imposed if a renewable policy target is not reached.
This table shows three optimal expansion planning setups constrained by different levels of risk in terms of *CVaR*. Risk increases as we move from left to right. Solar PV and solar CSP were defined in Table 1. Panels A and B show results for different penalties imposed for unmet energy demand.

	Optimal expansion planning setups constrained by different levels of risk in terms of CVaR																	
	Portfolio under minimum CVaR and maximum cost						Portfolio under intermediate CVaR and intermediate cost						Portfolio under maximum CVaR and minimum cost					
	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.
	Panel A: Opt. Portfolios with a policy target of 20% of non-conventional renewables and a penalty for lost load of 400 USD/MWh																	
Coal	2050	89.1%	4444	4444	2618	26.3%	1925	82.1%	4319	4319	2738	27.6%	1665	80.6%	4059	4059	2717	27.3%
Oil	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	0	0.0%
Hydro	262	0.0%	4315	1888	1888	19.0%	2947	1.3%	7000	3063	3046	30.6%	2947	1.5%	7000	3063	3044	30.6%
Wind	3366	0.0%	4000	1126	1126	11.3%	0	0.0%	634	179	179	1.8%	0	0.0%	634	179	179	1.8%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	69	0.7%	0	0.0%	2777	2777	85	0.9%	0	0.0%	2777	2777	121	1.2%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	0.0%	1000	850	850	8.6%	196	0.0%	700	595	595	6.0%	196	0.0%	700	595	595	6.0%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%
Solar CSP	200	0.0%	200	104	104	1.0%	0	0.0%	0	0	0	0.0%	0	0.0%	0	0	0	0.0%
Lost load						0.0%						0.0%						0.0%
Non-conv. renewables	7143	0.0%	8800	3294	3294	33.1%	3277	0.0%	4934	1988	1988	20.0%	3277	0.0%	4934	1988	1988	20.0%
All renewables	9440	0.0%	17115	7251	7250	73.0%	8259	0.5%	15934	7118	7101	71.5%	8259	0.5%	15934	7118	7099	71.4%
Fossil fuel + renewables	11490	15.9%	26639	16,774	9938	100.0%	10184	15.9%	25333	16,517	9924	99.9%	9924	14.0%	25073	16,257	9938	100.0%
Diversific. (total cap)				0.87						0.84						0.84		
Diversific. (total gen)				0.82						0.78						0.78		
MM tons CO_2e				22.84						23.81						23.77		
Exp. Cost [MM $]				6571						6215						6208		
CVaR [MM $]				7746						8054						8087		
	Panel B: Opt. Portfolios with a policy target of 20% of non-conventional renewables and a penalty for lost load of 100 USD/MWh																	
Coal	1222	44.9%	3616	3616	3068	30.9%	1161	17.1%	3555	3555	3356	33.8%	143	100.0%	2537	2537	2191	22.0%
Oil	0	0.0%	2303	2303	2	0.0%	0	0.0%	2303	2303	13	0.1%	0	0.0%	2303	2303	19	0.2%
Hydro	0	0.0%	4053	1773	1759	17.7%	509	5.8%	4562	1996	1983	20.0%	2947	1.7%	7000	3063	3041	30.6%
Wind	3366	0.0%	4000	1126	1126	11.3%	67	0.0%	701	197	197	2.0%	0	0.0%	634	179	179	1.8%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	41	0.4%	0	0.0%	2777	2777	180	1.8%	0	0.0%	2777	2777	271	2.7%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	66.7%	1000	850	569	5.7%	496	32.0%	1000	850	715	7.2%	224	11.0%	728	618	598	6.0%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%
Solar CSP	93	0.0%	93	49	49	0.5%	0	0.0%	0	0	0	0.0%	0	0.0%	0	0	0	0.0%
Lost load						0.4%						2.1%						3.6%
Non-conv. renewables	7036	4.7%	8693	3239	2958	29.8%	3644	4.4%	5301	2261	2126	21.4%	3305	0.7%	4962	2011	1990	20.0%
All renewables	9071	3.6%	16746	7080	6785	68.3%	6188	3.0%	13863	6325	6178	62.2%	8287	0.9%	15962	7142	7099	71.4%
Fossil fuel + renewables	10293	8.5%	25442	15,776	9895	99.6%	7349	5.3%	22498	14960	9727	97.9%	8430	2.6%	23579	14,759	9579	96.4%
Diversific. (total cap)				0.87						0.86						0.83		
Diversific. (total gen)				0.81						0.79						0.80		
MM tons CO_2e				26.41						29.37						20.10		
Exp. Cost [MM $]				6384						6184						6080		
CVaR [MM $]				7625						7701						7897		

Further, and as anticipated, CO_2e emissions decrease after imposing the environmental policy in Table 6, relative to the benchmark case presented in Table 5 that does not consider any environmental policy. In Panel A, which displays the optimal planning setup with minimum cost, CO_2e emissions decrease from 26.32 million tons in Table 5 to 23.77 million tons in Table 6, or by 9.7%.

The results in Table 6—from the hypothetical case of the Chilean penalty for unmet energy demand decreasing from US$400 in Panel A to US$100 in Panel B per MWh —are also noteworthy. As with Table 5, this change induces an increase in the average unsatisfied energy demand in Table 6. For instance, Panel B in Table 6 reveals that the unsatisfied energy demand reaches 3.6% in the optimal portfolio with minimum cost. This is because the energy production costs in some economic states increase to more than the penalty for unmet demand. This can be observed in scenarios in which the fossil fuel price for coal power increases to high levels. Similar to what we reported in Table 5, Table 6 indicates that the newly installed capacity for coal generation decreases from Panel A to Panel B; for example, in the optimal portfolios with a minimum cost, the newly installed capacity for coal generation is 1665 MWh in Panel A, but only 143 MWh in Panel B.

5.3. Optimal electricity generation planning with a carbon tax

In this section, we present an example of implementing an alternative policy measure to the one presented in Section 5.2, a carbon tax (see Eq. (18)). Before describing the result of optimal planning with a carbon tax, it is interesting to discuss some differences between the two environmental policies used in our study. First, and as we explained in Section 3.2, the policy regarding a minimum level of renewable generation involves a *one-off penalty* paid at the end of each period. Conversely, the carbon tax policy involves a *tax per carbon unit*, which is paid when the energy generation process produces CO_2e emissions.

Second, the policy regarding a minimum level of renewable generation only differentiates between two sub-groups of generating technologies: renewable and non-renewable (fossil fuel) technologies. However, the technologies within each group can significantly differ in terms of their CO_2e emissions, as indicated (see the last column of Table 2). Thus, the model under this environmental policy may select generating technologies with the highest CO_2e emissions inside each group. Alternatively, a carbon tax policy has a larger negative effect on technologies that deliver more CO_2e emissions for energy production—independently if they involve renewables versus non-renewables—than generating technologies with fewer CO_2e emissions.

Thus, some evidence already exists for the different impacts from these two policy measures. For instance, Palmer and Burtraw (2005) observe that the policy of a minimum level of renewable generation creates a preference for some technologies with high CO_2e emissions over other forms of energy production, which is not observed with a carbon tax policy. In fact, they discover that a policy mandating a minimum level of renewables induces an increase in coal generation rather than gas power, although coal generation exhibits higher CO_2e emissions than plants based on gas technology. Additionally, Menanteau et al. (2003) and Fischer and Newell (2008) find that a minimum-renewable policy is less efficient than a carbon tax because the former involves higher net economic costs.

In terms of our model's results, we report optimal planning setups as in Table 5—in which we impose two levels of carbon tax: US$10 and US$20 per tons of CO_2e emissions—which are reported in Tables 7 and 8, respectively. It is noteworthy that a difference exists between the effects of a renewable policy target (see Table 6) and a carbon tax (see Tables 7 and 8), in terms of the proportions of electricity the different technologies generate. For instance, Panel A in Table 7 demonstrates that small hydro-power and biomass generation are triggered in the case of the optimal portfolios with minimum cost (on the right-hand side of the table), which is similar to the results from Panel A in Table 6. However, the different technologies' proportions of *use* change, as explained in the following paragraphs.

We can observe an increase in the newly installed capacity and generation of biomass from Panel A in Table 7 relative to Table 6, in the case of optimal portfolios with minimum cost. First, biomass generation increases because the technology has low carbon emissions and relatively low investment and operational costs (see Table 2). Second, this generating technology is also stable, as indicated by the first column in Table 1. Third, biomass increases in use due to the decrease in coal power's newly installed capacity and generation. For instance, the proportion of generation from coal power is 23% in Table 7, Panel A, in the optimal portfolio with minimum cost; in the same portfolio in Table 6, this proportion is 27.3%. This is primarily because coal generation involves a high cost associated with the carbon tax given its highest CO_2e emission factor among the generating technologies (see Table 2).

Consequently, coal generation is replaced by biomass, which is a low-carbon, relatively inexpensive, and stable generation technology. Coal generation is also replaced by gas power. These results are consistent with Palmer and Burtraw (2005), who demonstrate that a carbon tax reduces (increases) the use of coal (gas) generation, in relation to the policy of a minimum level of renewables. In fact, despite there being no newly installed capacity for the gas technology, in Table 7 Panel A, there is an increase in the generation from it (i.e. using the already installed capacity for gas generation from 2014), which has lower carbon emissions than the coal technology. For example, the gas generation reaches 2.6% in Table 7 Panel A in the optimal portfolio with minimum cost, while the same portfolio in Table 6 Panel A has 1.2% of generation coming from gas.

Table 8 reveals that the newly installed capacity and generation based on coal technology further decreases when a higher carbon tax is imposed. For instance, the newly installed capacity and proportion of generation from coal are 0.0 MWh and 15.3%, respectively, in the optimal portfolio with minimum cost in Panel A. In this portfolio, instead of coal power,

Table 7
Optimal expansion planning with a carbon tax of US$10/ton of CO_2e.
This table shows three optimal expansion planning setups constrained by different levels of risk in terms of *CVaR*. Risk increases as we move from left to right. Solar PV and solar CSP were defined in Table 1. Panels A and B show results for different penalties imposed for unmet energy demand.

	Optimal expansion planning setups constrained by different levels of risk in terms of CVaR																	
	Portfolio under minimum CVaR and maximum cost						Portfolio under intermediate CVaR and intermediate cost						Portfolio under maximum CVaR and minimum cost					
	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.
Panel A: Opt. portfolios with a carbon tax (10 USD/ton CO_2e) a penalty for lost load of 400 USD/MWh																		
Coal	1839	100.0%	4233	4233	2108	21.2%	940	100.0%	3334	3334	1972	19.8%	675	100.0%	3069	3069	2290	23.0%
Oil	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	43	0.4%
Hydro	1516	0.6%	5569	2436	2432	24.5%	2947	1.7%	7000	3063	3041	30.6%	2947	1.9%	7000	3063	3038	30.6%
Wind	3366	0.0%	4000	1126	1126	11.3%	1938	0.0%	2572	724	724	7.3%	0	0.0%	634	179	179	1.8%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	36	0.4%	0	0.0%	2777	2777	84	0.8%	0	0.0%	2777	2777	256	2.6%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	0.2%	1000	850	849	8.5%	496	3.5%	1000	850	835	8.4%	496	0.0%	1000	850	850	8.6%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%
Solar CSP	200	0.0%	200	104	104	1.0%	0	0.0%	0	0	0	0.0%	0	0.0%	0	0	0	0.0%
Lost load						0.0%						0.0%						0.0%
Non-conv. renewables	7143	0.0%	8800	3294	3293	33.1%	5515	0.3%	7172	2788	2773	27.9%	3577	0.0%	5234	2242	2242	22.6%
All renewables	10694	0.1%	18369	7799	7794	78.4%	10497	0.6%	18172	7919	7882	79.3%	8559	0.7%	16234	7373	7349	73.9%
Fossil fuel + renewables	12533	14.8%	27682	17,112	9938	100.0%	11436	8.8%	26585	16,332	9938	100.0%	9234	7.9%	24383	15,522	9938	100.0%
Diversific. (total cap)				0.87						0.85						0.84		
Diversific. (total gen)				0.83						0.81						0.80		
MM tons CO_2e				18.51						17.54						21.09		
Exp. Cost [MM $]				6780						6482						6393		
CVaR [MM $]				8049						8332						8743		
Panel B: Opt. Portfolios with a carbon tax (10 USD/ton CO_2e) and a penalty for lost load of 100 USD/MWh																		
Coal	240	87.7%	2634	2634	2423	24.4%	0	0.0%	2394	2394	2005	20.2%	0	0.0%	2394	2394	2155	21.7%
Oil	0	0.0%	2303	2303	11	0.1%	0	0.0%	2303	2303	9	0.1%	0	0.0%	2303	2303	17	0.2%
Hydro	0	0.0%	4053	1773	1763	17.7%	2055	2.1%	6108	2673	2654	26.7%	2947	1.4%	7000	3063	3045	30.6%
Wind	3366	0.0%	4000	1126	1126	11.3%	1696	0.0%	2330	656	656	6.6%	0	0.0%	634	179	179	1.8%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	216	2.2%	0	0.0%	2777	2777	182	1.8%	0	0.0%	2777	2777	339	3.4%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	9.9%	1000	850	808	8.1%	496	17.3%	1000	850	777	7.8%	0	0.0%	504	428	403	4.1%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%
Solar CSP	0	0.0%	0	0	0	0.0%	200	0.0%	200	104	104	1.0%	0	0.0%	0	0	0	0.0%
Lost load						3.1%						2.7%						5.2%
Non-conv. renewables	6943	0.7%	8600	3190	3148	31.7%	5473	1.6%	7130	2824	2751	27.7%	3081	0.0%	4738	1821	1795	18.1%
All renewables	8978	0.5%	16653	7032	6980	70.2%	9564	1.3%	17239	7565	7473	75.2%	8063	0.5%	15738	6952	6908	69.5%
Fossil fuel + renewables	9218	2.8%	24367	14,746	9630	96.9%	9564	1.3%	24713	15039	9668	97.3%	8063	0.5%	23212	14,426	9419	94.8%
Diversific. (total cap)				0.87						0.86						0.83		
Diversific. (total gen)				0.84						0.83						0.81		
MM tons CO_2e				21.82						18.22						20.01		
Exp. Cost [MM $]				6532						6394						6273		
CVaR [MM $]				7862						8003						8164		

Table 8
Optimal expansion planning with a carbon tax of US$20/ton CO_2e.
This table shows three optimal expansion planning setups constrained by different levels of risk in terms of *CVaR*. Risk increases as we move from left to right. Solar PV and solar CSP were defined in Table 1. Panels A and B show results for different penalties imposed for unmet energy demand.

	Optimal expansion planning setups constrained by different levels of risk in terms of CVaR																	
	Portfolio under minimum CVaR and maximum cost						Portfolio under intermediate CVaR and intermediate cost						Portfolio under maximum CVaR and minimum cost					
	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen in MW	% of gen covered per each type of technol.	New cap in MW	Average % of new cap for generat. reserves	Total cap in MW	Average effective cap in MW	Average real gen per hour in MW	% of gen covered per each type of technol.
	Panel A: Opt. portfolios with a carbon tax (20 USD/ton CO_2e) a penalty for lost load of 400 USD/MWh																	
Coal	1737	100.0%	4131	4131	1713	17.2%	348	100.0%	2742	2742	1590	16.0%	0	0.0%	2394	2394	1524	15.3%
Oil	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	0	0.0%	0	0.0%	2303	2303	0	0.0%
Hydro	2548	0.9%	6601	2888	2878	29.0%	2947	2.2%	7000	3063	3034	30.5%	2947	2.5%	7000	3063	3031	30.5%
Wind	3366	0.0%	4000	1126	1126	11.3%	3366	0.0%	4000	1126	1126	11.3%	3366	0.0%	4000	1126	1126	11.3%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	11	0.1%	0	0.0%	2777	2777	94	0.9%	0	0.0%	2777	2777	164	1.6%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	6.1%	1000	850	824	8.3%	496	8.9%	1000	850	813	8.2%	496	8.9%	1000	850	813	8.2%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.9%	200	170	168	1.7%	200	0.9%	200	170	168	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%
Solar CSP	200	0.0%	200	104	104	1.0%	0	0.0%	0	0	0	0.0%	0	0.0%	0	0	0	0.0%
Lost load						0.0%						0.0%						0.0%
Non-conv. renewables	7143	0.4%	8800	3294	3269	32.9%	6943	0.6%	8600	3190	3151	31.7%	6943	0.7%	8600	3190	3151	31.7%
All renewables	11726	0.5%	19401	8251	8214	82.7%	11925	0.9%	19600	8321	8254	83.1%	11925	1.0%	19600	8321	8250	83.0%
Fossil fuel + renewables	13463	13.3%	28612	17,462	9938	100.0%	12273	3.7%	27422	16,143	9938	100.0%	11925	1.0%	27074	15,795	9938	100.0%
Diversific. (total cap)				0.86						0.85						0.85		
Diversific. (total gen)				0.82						0.81						0.81		
MM tons CO_2e				15.15						14.44						14.15		
Exp. Cost [MM $]				6920						6617						6575		
CVaR [MM $]				8362						8656						8803		
	Panel B: Opt. Portfolios with a carbon tax (20 USD/ton CO_2e) and a penalty for lost load of 100 USD/MWh																	
Coal	0	0.0%	2394	2394	2171	21.8%	0	0.0%	2394	2394	1902	19.1%	0	0.0%	2394	2394	1903	19.2%
Oil	0	0.0%	2303	2303	11	0.1%	0	0.0%	2303	2303	8	0.1%	0	0.0%	2303	2303	11	0.1%
Hydro	0	0.0%	4053	1773	1766	17.8%	1363	2.6%	5416	2370	2354	23.7%	2947	1.6%	7000	3063	3042	30.6%
Wind	3366	0.0%	4000	1126	1126	11.3%	3366	0.0%	4000	1126	1126	11.3%	0	0.0%	634	179	179	1.8%
Solar PV	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%	2431	0.0%	2600	630	630	6.3%
LNG	0	0.0%	2777	2777	268	2.7%	0	0.0%	2777	2777	158	1.6%	0	0.0%	2777	2777	216	2.2%
Run-of-river	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%	2035	0.0%	4000	2068	2068	20.8%
Biomass	496	1.4%	1000	850	844	8.5%	496	2.9%	1000	850	838	8.4%	496	2.8%	1000	850	838	8.4%
Geothermal	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%	200	0.0%	200	170	170	1.7%
Small hydro	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%	450	0.0%	800	414	414	4.2%
Solar CSP	0	0.0%	0	0	0	0.0%	0	0.0%	0	0	0	0.0%	155	0.0%	155	81	81	0.8%
Lost load						4.7%						2.7%						3.9%
Non-conv. renewables	6943	0.1%	8600	3190	3184	32.0%	6943	0.2%	8600	3190	3178	32.0%	3732	0.4%	5389	2323	2311	23.3%
All renewables	8978	0.1%	16653	7032	7018	70.6%	10341	0.5%	18016	7628	7600	76.5%	8714	0.7%	16389	7454	7421	74.7%
Fossil fuel + renewables	8978	0.1%	24127	14,506	9469	95.3%	10341	0.5%	25490	15,102	9668	97.3%	8714	0.7%	23863	14,928	9550	96.1%
Diversific. (total cap)				0.87						0.86						0.84		
Diversific. (total gen)				0.85						0.84						0.81		
MM tons CO_2e				19.94						17.29						17.51		
Exp. Cost [MM $]				6733						6617						6480		
CVaR [MM $]				8048						8105						8314		

there is additional newly installed capacity (3366 MWh) and a larger proportion of generation (11.3%) based on the wind technology, which has a low level of carbon emissions.

The allocation of technologies also changes from Tables 7 to 8 in the hypothetical case decreasing the Chilean penalty for unmet energy demand, from US$400 in Panel A to US$100 in Panel B per MWh of unsatisfied demand. As in Tables 5 and 6, in Panel B of Tables 7 and 8 this hypothetical change produces an increase in the average unsatisfied energy demand relative to the respective portfolios in Panel A. For example, the unsatisfied energy demand from Panel B in Table 7 is 5.2% in the optimal portfolio with minimum cost. As explained in previous sections, this occurs because it is preferable to pay the penalty for unmet demand in some economic states than to produce energy (especially through coal power since an additional large cost would have to be paid on that technology due to the carbon tax, given its high levels of carbon emissions). For instance, in Table 7, in the optimal portfolios with minimum cost, the newly installed capacity for coal generation is 675 MWh in Panel A, but 0.0 MWh in Panel B.

It is also noteworthy that Tables 7 and 8 reveal—as in Table 5—that the newly installed capacity and generation from hydro-reservoir technology decrease as optimal portfolios with less risk are considered (moving from right to left). However, this decrease is lower in Tables 7 and 8 than in Table 5. For instance, in the portfolio with minimum *CVaR* in Table 5 Panel A (i.e. left-hand side of table) the newly installed capacity and proportion of generation of the hydro-reservoir technology are 262 MWh and 19.0%, respectively, while those figures in Table 7 Panel A are respectively 1516 MWh and 24.5%, for the same type of portfolio. This is because, in Tables 7 and 8, in all portfolios, the level of *newly* installed capacity of coal power is lower than in the benchmark case (given its high levels of carbon emissions that are punished with the carbon tax). Thus, hydro-reservoir power partially covers the decrease in the use of the coal technology when considering generation portfolios with less risk.

In term of the use of new forms of energy, we can observe that, in general, there is an increase in the use of non-conventional renewable generation in Tables 7 and 8, in relation to the benchmark case in Table 5. For instance, in the optimal portfolio with minimum cost, Table 5 Panel A reports a newly installed capacity and proportion of generation of non-conventional renewable power of 2631 MWh and 16.0%, respectively. In the equivalent portfolio in Table 7 Panel A, those figures become 3577 MWh and 26.6%, respectively.

Consequently, the system's level of diversification increases in Tables 7 and 8 relative to Table 5, given the greater use of non-conventional renewable generation as described in the previous paragraph. For example, the optimal portfolio with minimum cost in Panel A, Table 5, has a $Diversific.(total\ cap) = 0.83$ and $Diversific.(total\ gen) = 0.77$; these become 0.84 and 0.80, respectively, in Table 7, Panel A.

Given that the diversification is higher in Tables 7 and 8, the risk levels should be lower relative to the benchmark setup in Table 5. Thus, and as explained in Section 5.1, we evaluate the risk reductions in Tables 7 and 8 relative to Table 5 by calculating the ratio $(CVaR - Exp.\ Cost)/Exp.\ Cost$, since the additional costs associated with the carbon tax could distort the *CVaR*. For example, this ratio for the optimal portfolio with minimum cost as noted in Panel A, Table 5 is 0.378 with no environmental policy; meanwhile, the ratios are 0.368 and 0.339 for the equivalent portfolios in Panel A in Tables 7 and 8, or when taxes of US$10 and US$20 per ton of CO_2e are applied, respectively.

The risk level decreases in Tables 7 and 8 due to the diversification relative to the benchmark optimal portfolios in Table 5; thus, the expected system costs should increase, as explained in Sections 5.1 and 5.2. However, it would be unreasonable to use the expected costs reported in Tables 7 and 8, as they include the additional costs associated with the carbon tax, while those in Table 5 do not. For instance, in the optimal portfolio with minimum cost of Table 7 Panel A, the expected cost is US$6393 million, which includes US$211 million from the carbon tax (i.e. 21.09 million tons of CO_2e * US$10 per ton of CO_2e = US$211 million).

Thus, without considering the costs associated with the carbon tax, this portfolio in Table 7, Panel A has an adjusted expected cost of US$6.182 million (i.e. US$6393 million − US$211 million = US$6182 million), which is US$32 million higher than that of the equivalent portfolio in Table 5 Panel A. This increase of US$32 million is due to the fact that, when a carbon tax is applied, small hydro and biomass installed capacities increase to replace part of the coal capacity, where the latter is reduced due to the carbon tax, as described above. Small hydro and biomass generating technologies are more expensive than coal power (see Table 2), which increases costs; however, they produce lower levels of CO_2e emissions than coal power. Consequently, reductions in carbon emissions come at a higher cost when also considering energy production stability.

Moreover, expect costs of the system with a carbon tax policy are lower than a policy of minimum level of renewables, which is consistent with Fischer and Newell (2008). For instance, as explained in the previous paragraph, the adjusted expected cost of US$6182 million on the right hand side of Table 7 Panel A is lower than the respective expected cost in Table 6 (i.e. US$6208 million).

We also observe that the carbon tax policy reduces more the CO_2e emissions than the policy of minimum level of renewable, which is in line with the findings of Palmer and Burtraw (2005). For example, there are 23.77 million tons of CO_2e in the optimal planning setup with minimum cost in Table 6 Panel A, but 21.09 and 14.15 million tons of CO_2e in the respective portfolios when carbon taxes of US$10 (Table 7 Panel A) and US$20 (Table 8 Panel A) per ton of CO_2e are applied, respectively. This is because the carbon tax is a *per-carbon-unit tax* that is paid whenever energy production involves CO_2e emissions. Thus, a carbon tax has a high negative effect on technologies with the largest CO_2e emissions. Conversely, the policy of a minimum level of renewable generation entails a *one-off penalty*, and it only differentiates between two subgroups: 'non-conventional' renewable technologies and other technologies. Nevertheless, as previously explained, this policy does not discriminate between the levels of CO_2e emissions coming from the different generating technologies within each sub-group.

We can also compare the reductions of carbon emissions obtained in Tables 7 and 8 in relation to Table 5. For instance, Table 5 Panel A shows 26.32 million tons of CO_2e in the optimal portfolio with minimum cost, while the same portfolio in Table 7 Panel A has 21.09 million tons of CO_2e. Thus, in this case, we observe a reduction in emissions of 5.23 million tons of CO_2e between Tables 5 and 7. In addition, the expected costs of those portfolios are US$6150 million in Table 5 Panel A and US$6393 million in Table 7 Panel A, which is an increase of US$243 million. Thus, we can consider the cost of reducing emissions by 5.23 million tons of CO_2e to be US$243 million, which corresponds to a massive value of US$46.46 per ton of CO_2e (i.e. US$243 million/5.23 million tons of CO_2e = US$46.46 per ton of CO_2e), and this value is much larger than the carbon tax used in Table 7.

However, the analysis described in the previous paragraph has a problem, as has already been explained in this section: the expected costs in Table 7 already include the additional costs associated with the carbon tax, which is not the case for the expected costs in Table 5. Thus, it may be unfair to compare expected costs between Tables 5 and 7. Therefore, an improved analysis is the following. In the optimal portfolio with minimum cost of Table 7 Panel A, the expected cost is US$6393 million, but this expected cost already includes US$211 million from the carbon tax (i.e. 21.09 million tons of CO_2e * US$10 per ton of CO_2e = US$211 million). Thus, without considering the costs associated with the carbon tax, this portfolio has an adjusted expected cost of US$6182 million (i.e. US$6393 million − US$211 million = US$6182 million). Consequently, the comparable values of expected costs for these two portfolios in Tables 5 and 7 are US$6150 million and US$6182 million, respectively, giving an increase of US$32 million when we move from Tables 5 to 7. This increase in the expected cost implies a value of US$6.11 per ton of CO_2e (i.e. US$32 million/5.23 million tons of CO_2e = US$6.11 per ton of CO_2e), which is an efficient use of the power allocation under the renewable policy of a carbon tax.

We can also think about this analysis, with the adjustment in expected cost, in a different way. For instance, we can include *ex post* a carbon tax on the optimal expansion planning setup without environmental policies from Table 5, which is reflected in Table 9. Thus, the tables with and without a carbon tax are comparable.

This table shows an analysis of the inclusion of a carbon tax *ex post* in the extreme expansion planning setups without environmental policies from Table 5. Thus, we apply an ex-post carbon tax to the following portfolios of Table 5: the portfolio with minimum *CVaR* and the portfolio with minimum cost. In this ex-post analysis, we use two levels of carbon tax: US$10 and US$20 per ton of CO_2e emitted. We can observe that Tables 7 and 8 have lower expected costs than Table 9. This means that Tables 7 and 8 make efficient optimal decisions, which take the imposed carbon tax into consideration in an optimal way.

6. Conclusion

This work analyzed environmental policies' effects on private investors' investment decisions regarding future energy generation. Specifically, we presented a model for optimal expansion planning under environmental policies that considers the system's production costs and risks. The model allows for the possibility of installing diverse renewable and non-renewable technologies, and considers investment and operational costs as well as the penalties associated with unsatisfied demand. The risks are associated with unexpected changes in economic variables and intermittent renewable generation. In implementing the model, we obtained optimal expansion-planning setups under cases involving different environmental policies.

We demonstrated that environmental policies can induce benefits in terms of reducing a system's risks when diverse renewable technologies are used simultaneously. If a private investor has multiple generating technologies, each technology is an asset that forms part of a large portfolio. Given that the current energy systems around the world are mainly based on a few generating technologies (e.g. hydro and fossil fuel power), if an investor wants to reduce risk through diversification, she/he has to install and produce electricity through new forms of generation (e.g. small hydro, solar photovoltaic (PV), wind, biomass, geothermal, and concentrated solar power (CSP)). Thus, through the diversification of generating technologies, the private investor can reduce her/his risk exposure.

When investors face environmental policies, such low-carbon policies by default induce a diversification of generating technologies. This is because environmental policies cause increases in the installed capacity and generation of *new forms* of energy production (i.e. new renewable generating technologies), which increases the diversification. Thus, in a diversified portfolio of energy production, each generating technology can be used to hedge the risks of other generating technologies, which induces a reduction in the risk of the whole energy production system.

Consequently, carbon-reduction policies can be economically justified from a risk-reduction perspective by using basic diversification gains. Our model is simple and intuitive, and can be implemented by private investors in different countries or regions. Nevertheless, compelling issues remain to be addressed. For instance, future researchers could contribute to the model's flexibility by adding two or more stages to the decision-making process—and thus, considering progressive future changes in environmental regulations—and analyzing the optimal time to make investment decisions.

Table 9
Analysis of the inclusion *ex post* of a carbon tax in the optimal expansion planning setups without environmental policies.
This table shows an analysis of the inclusion *ex post* of a carbon tax in the extreme expansion planning setups without environmental policies from Table 5 (i.e. in this table, we apply a carbon tax on the results from Table 5 in the case of (i) the portfolio under minimum CVaR; and (ii) the portfolio under minimum cost.

	Analysis of including *ex-post* a carbon tax to optimal expansion planning without environmental policies							
	Portfolio under minimum CVaR and maximum cost				Portfolio under maximum CVaR and minimum cost			
	Exp. total cost of optimal planning in MM USD (i)	Emission in MM tons of CO_2e	Exp. cost from a carbon tax, *if such tax was applied*, in MM USD (ii)	Exp. total cost including *ex-post* carbon tax costs in MM USD (i)+(ii)	Exp. total cost of optimal planning in MM USD (i)	Emission in MM tons of CO_2e	Exp. cost from a carbon tax, *if such tax was applied*, in MM USD (ii)	Exp. total cost including *ex-post* carbon tax costs in MM USD (i)+(ii)
	Panel A: Opt. portfolios without environmental policies and a value of lost load of 400 USD/MWh							
Potential carbon tax (10 USD/ton CO_2e)	6571	22.84	228	6800	6150	26.32	263	6413
Potential carbon tax (20 USD/ton CO_2e)	6571	22.84	457	7028	6150	26.32	526	6677
	Panel B: Opt. portfolios without environmental policies and a value of lost load of 100 USD/MWh							
Potential carbon tax (10 USD/ton CO_2e)	6384	26.41	264	6648	6068	25.19	252	6320
Potential carbon tax (20 USD/ton CO_2e)	6384	26.41	528	6912	6068	25.19	504	6572

Appendix A

Considering unexpected contingencies: Unexpected contingencies such as the sudden failure of a generator, when there are no reserves, may negatively affect the electricity supply. In engineering terms, the effect of unexpected contingencies on the electricity supply is directly reflected in a reduction in system frequency.[21] The use of reserves to avoid the system frequency dropping below an accepted value is called primary frequency response (hereinafter referred to as *PFR*). Optimal expansion planning for electricity generation is adequate in terms of *PFR* if the system frequency does not drop below a given limit after any single generation contingency.

In the case of an unexpected contingency, spinning reserves are used for *PFR* (see Section 3.5), since they can quickly produce extra electricity because they are already online. Furthermore, we assume that there is a specific sub-group of spinning reserves that are used exclusively for this purpose. Let $R^{sp,PFR}_{i,j}(s)$ be the sub-group of spinning reserves exclusively allocated for *PFR* in year τ for technology i in hour j in state s (with $R^{sp,PFR}_{i,j}(s) \leq R^{sp}_{i,j}(s)$).

Suppose that the optimal set of primary reserves available in hour j in state s for each of the different technologies is $R^{sp,PFR}_{1,j}(s),\ R^{sp,PFR}_{2,j},(s)\ \ldots, R^{sp,PFR}_{i,j}(s)$. Let us assume that there is a large generation outage, Δ^E, measured in MW, which generates a drop in the system frequency; thus, we impose the following constraint on the security of the supply:

$$\Delta^E - DR^{PFR}_j \leq \sum_{i\in\ I} R^{sp,PFR}_{i,j}(s), \tag{A1}$$

where DR^{PFR}_j is the maximum amount of demand that is curtailable for primary frequency control in hour j. However, the security-of-supply constraint reflected in Eq. (A1) is a necessary, albeit insufficient, condition for maintaining the stability of the system, since the reaction speed of the reserves is not considered.

Suppose that $R^{sp,PFR}_{i,j}(s)$ is distributed among $n^{PFR}_{i,j}(s)$ generating units and has an 'emergency' ramp rate of $\rho_i^{;}$. Furthermore, suppose that the system has a feedback controller called the 'governor', which identifies changes in system frequency. The task of this governor is to trigger the use of reserves when it detects a drop in system frequency.[22]

We assume that the governor does not allow the frequency to drop below the level f_{MIN}. The governor's action also has a dead band, f_{db} (which is the interval in which no action is taken, when the change in the frequency is small), while the pre-contingency frequency is f_0.[23] Thus, we include the constraint presented in Chávez et al. (2014), who show that the total emergency ramp rate of reserves for a primary response, $\sum_{i\in I} n^{PFR}_{i,j}(s)\rho_i'$, in order to avoid a frequency level below f_{MIN}, has to satisfy the following restriction:

$$\frac{f_0\left(\Delta^E - DR^{PFR}_j\right)^2}{4(f_0 - f_{MIN} - f_{db})\left(\sum_i H_i n_{i,j}(s)\bar{P}_i - H_f\Delta^E\right)} \leq \sum_{i\in I} n^{PFR}_{i,j}(s)\rho_i', \tag{A2}$$

where H_i is the constant of inertia of units belonging to technology i, $\bar{P}_i$ is the maximum power output of each online generating unit, and H_f is the constant of inertia of the missing units that induce contingency Δ^E.[24]

The constraint proposed by Chávez et al. (2014), and described in Eq. (A2), reflects a restriction on the security of supply including reserves for all technologies in an aggregate way. Therefore, we also have to include constraints on the reserves based on each of the technologies connected to the system, so as to take into account differences in individual emergency ramp rates, with the objective of improving the security of supply of the system. Let T^{MIN} be the time after which the frequency stops dropping, after contingency Δ^E, due to the use of primary reserves, defined as $T^{MIN} = (\Delta^E - DR^{PFR}_j)/\sum_i(n^{PFR}_{i,j}(s)\rho_i^{;})$. Let t^{MIN}_i be the time after which the primary reserves of technology i can reach their maximum generation output: $t^{MIN}_i = R^{sp,PFR}_{i,j}(s)/(n^{PFR}_{i,j}(s)\rho_i^{;})$. Thus, we impose that $t^{MIN}_i \leq T^{MIN}$ for all technologies used as reserves for *PFR*, which can be expressed as:

$$\frac{R^{sp,PFR}_{i,j}(s)}{n^{PFR}_{i,j}(s)\rho_i^{;}} \leq \frac{\Delta^E - DR^{PFR}_j}{\sum_i n^{PFR}_{i,j}(s)\rho_i^{;}}. \tag{A3}$$

Post-contingency recovery: After a contingency event, spinning reserves that are not used for *PFR*, $R^{sp}_{i,j}(s) - R^{sp,PFR}_{i,j}(s)$, help to drive the system frequency towards the pre-contingency value. We assume that the post-contingency recovery is achieved in a short period, since re-establishing normal operations is a priority for system performance. Thus, there is a maximum time by which reserves used for post-contingency recovery should have been dispatched. Let t^{sp}_i be the time in which

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[21] The frequency is the oscillation of alternating current (AC) in a power system. Depending on the country, the frequency is either 50 Hz or 60 Hz.

[22] Emergency ramp rates are the rates of change in the power outputs of the reserves set aside for *PFR* as used by the governor to maintain the security of supply.

[23] In the initial period following a contingency, there is a dead band in which the system frequency is controlled by the inertial response of the system.

[24] In constraint (A2), the expression $(\sum_i H_i \cdot n_{i,j,s} \cdot \bar{P}_i - H_f \cdot \Delta^E)$ is equal to the system's post-contingency kinetic energy, which determines the rate at which the system frequency will drop when facing a generation–consumption imbalance.

spinning reserves based on technology i, used for post-contingency recovery, deliver the maximum generation output, where $t_i^{sp} = (R_{i,j}^{sp}(s) - R_{i,j}^{sp,PFR}(s))/(n_{i,j}^{sp}(s)\rho_i)$. Thus, we assume that:

$$t_i^{sp} \leq t_i^{sp*}, \tag{A4}$$

where t_i^{sp*} is the maximum time it takes to restore the system frequency to the pre-contingency level.

Forecasting errors under intermittency of renewable generation and changes in demand: In each hour of state s, we can observe imbalances in the supply and demand of electricity due to the stochastic components of the power system. From the perspective of the electricity supply, the capacity factor of a renewable technology, $CF_{i^R,j}(s)$, changes stochastically on an hourly basis, as explained in Section 3.3. Customer demand, $D_j(s)$, also changes stochastically over time. These supply–demand imbalances can increase both the level and the volatility of the cost associated with penalties for unsatisfied energy demand (see Eq. (2)).

In an ideal power system, in which plants can instantaneously generate electricity, imbalances in the supply and demand of electricity can be solved by instantaneous changes in electricity generation. However, in real power systems, it takes time for generating units to generate more electricity (see Section 3.4). Thus, the controllers of the power system can use forecasting tools to anticipate changes in future renewable capacity factors and/or in future demand levels.

We assume that changes in $CF_{i^R,j}(s)$ are not completely unexpected before hour j, since it is possible to perform weather forecasts using meteorological information and/or statistical techniques. Nevertheless, future values of $CF_{i^R,j}(s)$ are not perfectly predictable, since it is difficult to predict all atmospheric conditions (e.g. in the case of generation based on wind, it is difficult to forecast air density, wind speed and wind direction simultaneously). Thus, errors exist between the forecasted and realized maximum levels of generation.

Let $\Delta_{i^R,j}^{CF}(s) = CF_{i^R,j}^F(s) - CF_{i^R,j}(s)$ be the error between the forecasted capacity factor, $CF_{i^R,j}^F(s)$, and the realized capacity factor, $CF_{i^R,j}(s)$, for renewable technology i^R in hour j in state s. We assume that $\Delta_{i^R,j}^{CF}(s)$ is normally distributed with zero mean and standard deviation $\sigma_{i^R,j}(s)$; thus, $\Delta_{i^R,j}^{CF}(s) \sim N(0, \sigma_{i^R,j}(s))$. We assume that the potential unpredicted intermittency in generation, $\Delta_{i^R,j}^{g}(s)$, is constrained as follows:

$$\Delta_{i^R,j}^{g}(s) = g_{i^R,j}^F(s) - g_{i^R,j}(s) \leq 3.0 \cdot cap_{i^R} \cdot \sigma_{i^R,j}(s), \tag{A5}$$

where $g_{i^R,j}^F(s)$ and $g_{i^R,j}(s)$ are the forecasted and realized generation from using renewable technology i^R in hour j in state s. The expression in (A5) shows that unpredicted intermittency in generation would, in an extreme case, reach a maximum of $3.0 \cdot cap_{i^R} \cdot \sigma_{i^R,j}(s)$. This is derived from a combination of (i) assuming that a large forecasting error can happen with a 0.13% probability (where we use the inverse of a normal distribution, $N(0,1)$, with a 0.13% probability, which provides a value of 3.0), and (ii) using the constraint in (19), since $\sigma_{i^R,j}(s)$ is the volatility of the forecasting errors of $CF_{i^R,j}(s)$. Thus, we can write an expression for the constraint on the total unpredicted intermittency of generation:

$$\sum_{i^R=1}^{I^R} \Delta_{i^R,j}^{g}(s) \leq 3.0 \cdot \sqrt{\sum_{i^R=1}^{I^R} \left(cap_{i^R} \cdot \sigma_{i^R,j}(s)\right)^2 + \left(\sigma_{D,j}(s)\right)^2}, \tag{A6}$$

where I^R is the total number of renewable technologies and $\sigma_{D,j}(s)$ is the standard deviation of the forecasting error between forecasted and realized demand (i.e. electricity demand can also be forecasted using statistical tools). In expression (A6), we assume that the forecasting errors in the renewable technologies' capacity factors are uncorrelated with each other and also with the forecasting error for the demand.

We use expression (A6) to impose a constraint on the minimum level of standing reserves, $R_{i,j}^{st}(s)$, and the level of spinning reserves that are not used for PFR, $R_{i,j}^{sp}(s) - R_{i,j}^{sp,PFR}(s)$, as follows:

$$\begin{aligned}&\left(\Delta^E - DR_j^{FE} + 3.0 \cdot \sqrt{\sum_{i^R=1}^{I^R} \left(cap_{i^R} \cdot \sigma_{i^R,j}(s)\right)^2 + \left(\sigma_{D,j}(s)\right)^2}\right) \\ &\quad \leq \sum_{i \in I} \left(R_{i,j}^{sp}(s) - R_{i,j}^{sp,PFR}(s)\right) + \sum_{i \in I} R_{i,j}^{st}(s).\end{aligned} \tag{A7}$$

Here, DR_j^{FE} is a parameter that accounts for the maximum amount of demand that is curtailable in hour j in order to support the system response to unexpected intermittency in renewables' generation and demand changes. It is important to notice that a potential system contingency, Δ^E, is part of constraint (A7). This is because spinning reserves that are not used for PFR, $R_{i,j}^{sp}(s) - R_{i,j}^{sp,PFR}(s)$, are not only triggered to control forecasting errors in renewable generation intermittency and demand changes. These spinning reserves also help post-contingency recovery to drive the system frequency towards the pre-contingency value, as explained in expression (A4). Thus, post-contingency recovery is also considered in Eq. (A7).

In the model implementation (see Section 4), we consider the possibility of forecasting the behavior of the capacity factors of the renewables and the behavior of customer demand. In our conversations with the team at the dispatch center which manages the Chilean CIS, they told us that the main forecasting errors derive from predictions of solar radiation and wind power (which affect the solar PV, CSP and wind technologies). Conversely, forecasts regarding hydrological conditions are generally quite accurate, since water inflows mainly derive from snowmelt water, which is induced by the atmospheric temperature several hours earlier; thus, they can be forecasted with a high degree of precision. Furthermore, in hydro-reservoir plants, the same reservoir can be used as a buffer for changes in water inflows. In terms of forecasting errors in electricity demand, the demand can also be predicted with a high degree of accuracy, since the main factors are the type of day (working or weekend), sunrise and sunset times, and atmospheric temperature (which can be forecasted with reasonable exactitude).[25]

Consequently, we focus on errors related to the forecasting of solar radiation and wind power. Nevertheless, the selection of optimal forecasting techniques is beyond the scope of this work, so we use a simple, albeit reasonable, criterion in implementing this model. In forecasting the solar capacity factor, we use the fact that solar radiation is quite stable (at least in Chile) in terms of its behavior in each season. Thus, we calculate the average hourly profile in each season of the representative year, and use this as a forecast for the following day in the respective season. In forecasting the wind capacity factor, we cannot use the same approach, since wind power can differ quite considerably from one hour to the next. Thus, we assume that wind conditions in hour j are persistent, and predict wind characteristics up to four hours later (i.e. the wind capacity factor in hour $j+4$ is the same as the current wind capacity factor in hour j).

Despite the fact that we assume perfect predictability of changes in the capacity factors of the other renewable technologies and in electricity demand, these variables are still stochastic. Therefore, the power system may still need additional backup (in terms of additional installed capacity from stable technologies) for any times when there are significant reductions in renewable capacity factors and/or significant increases in electricity demand. This backup is crucial to reducing the intermittency risk.

Model linearization: Our model is very rich in terms of reflecting the reality of the power system, including constraints on maintaining the security of the electricity supply. However, some of these constraints contain non-linear relationships. In this appendix, we describe the linearization of the non-linear constraints, which allows us to use Benders' decomposition to make the optimization problem computationally tractable.

In the case of constraints (24) and (25), they are non-linear because they contain the min(·) function. Nevertheless, these constraints can be linearized using an auxiliary variable, $n_{i,j}^{min}(s)$, which takes the minimum of the number of online units of technology i in two consecutive hours, as follows:

$$g_{i,j}(s) - g_{i,j-1}(s) \leq n_{i,j}^{min}(s) \cdot \rho_i + \left(n_{i,j}(s) - n_{i,j-1}(s)\right) \cdot \underline{P}_i \tag{A8}$$

$$g_{i,j-1}(s) - g_{i,j}(s) \leq n_{i,j}^{min}(s) \cdot \rho_i + \left(n_{i,j-1}(s) - n_{i,j}(s)\right) \cdot \underline{P}_i \tag{A9}$$

$$n_{i,j}^{min}(s) \leq n_{i,j}(s) \tag{A10}$$

$$n_{i,j}^{min}(s) \leq n_{i,j-1}(s) \tag{A11}$$

thus, constraints (A8)–(A11) are used in the model rather than constraints (24) and (25).

Constraint (A2) is also non-linear. However, we can obtain a linear approximation using a Taylor expansion. Let us assume that spinning reserves can be divided into three groups in hour j and state s: (i) fast generating units based on technologies $n_{FT,j}(s)$ with high emergency ramp rates, which are used in *PFR*, where the emergency ramp rate is assumed to be constant for all units and equal to ρ_{FT}; (ii) slow generating units based on technologies $n_{ST,j}(s)$ with low emergency ramp rates, which are used in *PFR*, where the emergency ramp rate is again assumed to be constant for all units but equal to ρ_{ST}; and (iii) generating units that do not participate in *PFR*, $n_{NPFR,j}(s)$. Thus, we have:

$$n_{FT,j}(s) = \sum_{i \in I^{FT}} n_{i,j}^{PFR}(s) \tag{A12}$$

$$n_{ST,j}(s) = \sum_{i \in I^{SL}} n_{i,j}^{PFR}(s) \tag{A13}$$

$$n_{NPFR,j}(s) = \sum_{i \in I^{NPFR}} n_{i,j}^{NPFR}(s), \tag{A14}$$

where I^{FT} and I^{ST} are the number of generating units used in *PFR* which are classified as fast and slow response units, respectively, and I^{NPFR} is the number of generating units that are not part of *PFR*. Let us also assume that the constant of inertia, H_i, and the maximum power output, $\bar{P}_i$, are equal for all generating technologies (i.e. $H = H_i = H_f$ and $\bar{P} = \bar{P}_i$). Thus, we can rewrite constraint (A2) as:

$$\frac{f_0\left(\Delta^E - DR_j^{PFR}\right)^2}{4(f_0 - f_{MIN} - f_{db})\left(\left(n_{FT,j}(s) + n_{ST,j}(s) + n_{NPFR,j}(s)\right)H\bar{P} - H\Delta^E\right)} \leq \left(n_{FT,j}(s)\rho_{FT} + n_{ST,j}(s)\rho_{ST}\right), \tag{A15}$$

[25] In Chile, atmospheric temperature can be forecasted with a high degree of accuracy in each season, unlike solar radiation. Solar radiation depends on the number of clouds in the atmosphere. However, the number of clouds depends on wind direction and the strength of the wind, which are more difficult to predict.

Table A1
Additional parameter values. The table shows additional parameters used in the model implementation. The initials p.u. refer to per unit.

Symbol	Description	Value	Unit
$\bar{P}$	Maximum power output of generic unit	400	MW
$\underline{P}_i$	Minimum unit output	160 for thermal 40 for hydro	MW
ρ_i	Hourly ramp rate	40 for coal 240 for oil, geothermal 200 for LNG, biomass, coal 360 for hydro	MW/h
$\rho_i^{\cdot}$	Emergency ramp rate	38 for thermal plants 8 for hydro-plants	MW/s
f_0	Nominal system frequency	50	Hz
f_{db}	Governor frequency dead band	±25	mHz
f_{MIN}	Minimum frequency allowed	49.2	Hz
H_f	Inertia constant of generic unit	5	s
λ	Factor of losses of stored water due to evaporation and/or seepage in the reservoir	0.005	p.u.
v^u	Upper bound of stored water	10,321	MMm^3
v^d	Lower bound of stored water	1556	MMm^3
η	Average inflow-to-power rate	1.9	MWh/hm^3
Δ^E	Size of largest generation outage	400	MW
$t^i_{MIN,db}$	Deployment time of operating reserves	0.25	h
DR_j^{FE}	Amount of curtailable demand to adjust the system in the case of forecasting errors or an unexpected contingency	200	MW
DR_j^{PFR}	Amount of curtailable demand for the primary frequency control	200	MW
dc^-	Cost of demand decrease	1	\$/MW
dc^+	Cost of demand increase	2	\$/MW
q^-	Maximum fraction of demand that can be decreased	5%	p.u.
q^+	Maximum fraction of demand that can be increased	5%	p.u.
σ_{WND}	Standard deviation of wind forecasting errors in all hours	12.8%	p.u.
$\sigma_{SOL,j}$	Standard deviation of solar forecasting errors in hour j	0–10.6%	p.u.
t_i^{sp*}	The maximum time it takes spinning reserves to generate the ceiling reserve availability	15 min	p.u.

or, equivalently,

$$\mathcal{F}\Big(n_{FT,j}(s), n_{ST,j}(s)\Big) \leq n_{NPFR,j}(s), \tag{A16}$$

where

$$\mathcal{F}\Big(n_{FT,j}(s), n_{ST,j}(s)\Big) = \frac{f_0\left(\Delta^E - DR_j^{PFR}\right)^2}{4(f_0 - f_{MIN} - f_{db})\left(n_{FT,j}(s)\rho_{FT} + n_{ST,j}(s)\rho_{ST}\right)H\bar{P}} - n_{FT,j}(s) - n_{ST,j}(s) + \frac{\Delta^E - DR_j^{PFR}}{\bar{P}}. \tag{A17}$$

We can obtain a linear version of Eq. (A17) by taking the first-order Taylor approximation of $\mathcal{F}(n_{FT,j}(s), n_{ST,j}(s))$, evaluated at the values where $n_{FT,j}(s) = a_1$ and $n_{ST,j}(s) = a_2$. We can use a linear approximation through a Taylor expansion, since $\mathcal{F}(n_{FT,j}(s), n_{ST,j}(s))$ is convex in both $n_{FT,j}(s)$ and $n_{ST,j}(s)$. The first-order Taylor expansion of Eq. (A17), $\mathcal{F}^T(\cdot)$, is:

$$\mathcal{F}^T\Big(n_{FT,j}(s), n_{ST,j}(s)\Big) = \mathcal{F}(a_1, a_2) + \Big(n_{FT,j}(s) - a_1\Big)\frac{\partial \mathcal{F}(a_1, a_2)}{\partial n_{FT,j}(s)} + \Big(n_{ST,j}(s) - a_2\Big)\frac{\partial \mathcal{F}(a_1, a_2)}{\partial n_{ST,j}(s)}. \tag{A18}$$

Then, the linear version of constraint (A2) becomes:

$$\mathcal{F}^T\Big(n_{FT,j}(s), n_{ST,j}(s)\Big) \leq n_{NPFR,j}(s). \tag{A19}$$

Another non-linear constraint is described in (A7). Constraint (A7) is not linear but has a convex function. Thus, we can again use a Taylor expansion to obtain a linear version of it, rewriting it as:

$$\mathcal{G}(cap_1, \ldots, cap_{I^R}) \leq \sum_{i \in I}\Big(R_{i,j}^{sp}(s) - R_{i,j}^{sp,PFR}(s)\Big) + \sum_{i \in I} R_{i,j}^{st}(s) - \Delta^E + DR_j^{FE} \tag{A20}$$

with

$$\mathcal{G}(cap_1, \ldots, cap_{I^R}) = 3.0 \cdot \sqrt{\sum_{i^R=1}^{I^R}\Big(cap_{i^R} \cdot \sigma_{i^R,j}(s)\Big)^2 + \Big(\sigma_{D,j}(s)\Big)^2}. \tag{A21}$$

We write a linear version of expression (A21) using the first-order Taylor approximation evaluated at points $b_{i^R} \in \{b_1, \dots, b_{I^R}\}$ corresponding to the set of renewable capacities $cap_{i^R} \in \{cap_1, \dots, cap_{I^R}\}$, respectively. Thus, the first-order Taylor expansion is:

$$\mathcal{G}^T(cap_1, \dots, cap_{I^R}) = \mathcal{G}(b_1, \dots, b_{I^R}) + \sum_{i^R=1}^{I^R} (cap_{i^R} - b_{i^R}) \frac{\partial \mathcal{G}(b_1, \dots, b_{I^R})}{\partial cap_{i^R}}. \tag{A22}$$

Therefore, the linear approximation of constraint (A7) is:

$$\mathcal{G}^T(cap_1, \dots, cap_{I^R}) \leq \sum_{i \in I} \left(R^{sp}_{i,j}(s) - R^{sp,PFR}_{i,j}(s) \right) + \sum_{i \in I} R^{st}_{i,j}(s) - \Delta^E + DR^{FE}_j. \tag{A23}$$

The last non-linear constraint in the model is expression (A3). However, this constraint is not convex; thus, a first-order Taylor expansion cannot be used to give a linear approximation. In this case, we impose that only one generating technology is used as a reserve for the *PFR*. This simplifies expression (A3), which ends up being a linear equality: $\Delta^E - DR^{PFR}_j = R^{sp,PFR}_{i^*,j}(s)$. This is because, from constraint (A1) we have $\Delta^E - DR^{PFR}_j \leq R^{sp,PFR}_{i^*,j}(s)$; and from expression (A3) we have $R^{sp,PFR}_{i^*,j}(s) \leq \Delta^E - DR^{PFR}_j$. We obtain several optimal planning expansions while assuming that each technology in turn is the only one used as a reserve for the *PFR*. The optimal solution is then the one that provides the lowest expected cost for a certain level of risk.

As a robustness check, we calculate a lower-bound solution of the model by removing constraint (A3). This lower-bound solution comes from a model that is less constrained. Thus, the optimal expansion plan obtained from this setup reflects a power system with lower expected costs, but this solution may violate constraint (A3) in some extreme scenarios. We compare the optimal solution when we impose that only one technology is used as a reserve for *PFR* (as explained in the previous paragraph) to the lower-bound solution in which we remove constraint (A3). The average difference in the expected cost of the system, between the two cases, is less than 0.3% for any risk level. Therefore, the assumption that only one generating technology is used as a reserve for *PFR* does not take us too far away from the real optimal solution.

Additional parameter values: In Table A1, we report additional parameters used in the model implementation. The values were selected according to regulations and standards in the Chilean power sector, which were obtained from the Chilean Ministry of Energy and the Chilean National Commission of Energy.

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