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The importance of time resolution, operational flexibility and risk aversion in quantifying the value of energy storage in long-term energy planning studies

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A B S T R A C T

This paper analyzes the impact of modeling detail in long-term energy planning models when assessing the value of energy storage in electricity markets. By running six optimization models for the long-term planning of combined generation and storage installed capacities in the Chilean electricity system (each with different levels of detail/complexity in terms of time resolution, recognition of operational inflexibility —i.e. technical constraints of power plants— and recognition of uncertainty in fossil fuel prices), we determine six portfolio solutions with significantly different levels of energy storage installed capacity. Furthermore, we found that the total installed capacity of storage plants escalates when increasing the level of modeling complexity, which can be achieved by augmenting the time resolution and the number of constraints that better recognize the inflexibility of generation plants and by acknowledging the presence of long-term uncertainties associated with fossil fuel prices fluctuations. In our particular study, we found a difference of more than an order of magnitude between the amount of installed capacity of storage plants determined by the detailed model (that with hourly resolution and full consideration of technical constraints of power plants) and that obtained by the planning model that adopts the traditional assumptions commonly utilized in regulatory offices around the word (i.e. low time resolution and no recognition of technical/unit commitment constraints and uncertainty). Particularly, we found that the traditional, simplified solution can deliver an installed capacity of storage plants as low as 240 MW (~1.3% of estimated peak demand), while one of the most sophisticated solutions (which recognizes technical constraints of generating units, but ignores risks) delivers 7.8 GW (~41.7% of estimated peak demand). Moreover, by running a risk-constrained stochastic planning model, we also determine a risk-averse portfolio solution, which demonstrated the increased value of energy storage capacity in reducing electricity cost risk.

1. Introduction

Long-term energy planning models are typically used to determine efficient pathways for decarbonization of the energy sector and to analyze energy policies [1]. These tools are designed as optimization models, capable of computing the long-term economic equilibrium of energy markets (i.e. regarding investment and operation, usually minimizing costs) within a certain jurisdiction, given a set of physical, environmental and policy constraints and a set of deployable technologies [2].

In the last decade, renewable energy sources for electricity generation have become a central focus of study in the energy planning context [1,3], mainly due to the widespread concern about society's impact on the environment and to the recent cost decrease these technologies have exhibited. Some of these generating sources pose several challenges for energy planning models. For instance, the assessment of solar photovoltaics and wind farm costs in the planning timescale, requires detailed temporal, spatial and technical modeling [1,4], due to the variable and low predictability character of these resources. This detailed modeling may significantly increase calculation

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times, demanding the development of clever simplifications and/or advanced optimization techniques [2,3].

Energy storage has recently been studied in the energy planning context [5–11]. These technologies provide a low-carbon resource capable of complementing variable renewable energy (VRE[1]) [12,13]. For instance, this type of generation assets may help dealing with the variable character of VRE sources due to their ability of charging at times of energy surplus and discharging at times of energy scarcity [14–16]. Additionally, these plants may also aid in the management of VRE unpredictability, through the provision of operating reserves [17–19]. Due to this synergy between energy storage and VRE, an adequate assessment of the economic value of energy storage technologies necessarily requires an accurate representation of the variability and uncertainty inherent to VRE in energy planning models [20].

Despite the variety of studies showing the relevance of adequate representation of VRE and operational flexibility in long-term energy planning models [1,21–24], optimization tools utilized for policy studies across several countries are yet to incorporate sufficient modeling detail, as will be shown in the upcoming section. Hence, this paper aims at analyzing the importance of modeling complexity in assessing the value of energy storage in the presence of VRE. Here we explore three modeling aspects typically analyzed in the energy planning literature: time resolution (i.e. the number of time snapshots[2] in which each simulated year is divided), operational flexibility (i.e. modeling of technical constraints of power plants, unit commitment decisions, system security requirements, etc.) and the modeling of uncertainty in generating costs (e.g. fossil fuel prices).

By running several long-term planning models of the Chilean electricity generation sector, each with increasing modeling detail, we show that considering greater levels of modeling complexity in long-term energy planning models may directly translate into higher estimated investment in energy storage and economic value of these technologies. Moreover, by incorporating fossil fuel prices scenarios and determining a risk constrained portfolio of generating plants, we analyze, for the first time, the role that energy storage plays in hedging risk against uncertain fuel prices in the energy planning timescale. We thus conclude that modeling complexity is key to adequately assess the value that energy storage provides to energy systems.

The present paper is organized as follows. Section 2 summarizes the current practices and the state of the art regarding long-term energy planning models both in the academic and policy analysis contexts. Section 3 presents the methodology employed in this paper and Section 4 details calculations results and discussion. Finally, Section 5 shows the concluding remarks and policy implications of our study.

2. Current practices and the state of the art

Recent studies have analyzed and proposed modeling methods for a more precise incorporation of VRE technologies in energy planning models. Regarding temporal resolution [22,23], concluded that a low temporal detail in this type of models may lead to an overestimation of the efficient capacity of variable renewable generation. Moreover, reference [1] suggested that adequately modeling temporal resolution in energy planning models becomes more important than operational flexibility when facing high shares of renewables and proposed time modeling techniques based on representative days and residual load duration curves.

Other studies have assessed the relevance of modeling operational flexibility in long-term energy planning models [5,25–27]. For instance Ref. [25], proposed that energy planning models that do not account for the discrete character of unit-commitment decisions are inadequate to assess the cost of increased shares of VRE (i.e. wind). In a similar fashion, reference [5] studies the role of energy storage technologies when considering detailed operational constraints in the energy planning timescale. This work shows that if these constraints are considered, energy planning models are capable of better assessing storage technologies' ability of reducing electricity generation costs and displacing other flexible power plants. Reference [26] on the other hand, analyzes planning of transmission, generation and energy storage infrastructure simultaneously, considering unit-commitment constraints. The study concludes that significant value can be drawn from storage due to its contribution to transmission investment deferral.

A different group of studies has developed energy planning models capable of capturing VRE ability to hedge certain risks inherent to thermal and hydrothermal power systems. Building upon financial risk assessment techniques (such as modern portfolio theory and conditional value-at-risk optimization [28]), these works state that the consideration of uncertainty in fossil fuel prices and hydrological conditions in energy planning models may drive higher efficient shares of VRE, when also accounting for risk aversion of agents [21,29–32]. To our knowledge, no previous study has analyzed the role energy storage may play in risk-constrained generating portfolios.

Despite these advances in the academic literature, energy planning models currently utilized in energy policy studies have yet to incorporate sufficient modeling detail to assess VRE integration costs and consequently, to adequately quantify the value of energy storage in the planning framework.

For instance, Ref. [33] analyzes four relevant energy planning models utilized in the US: The Integrated Planning Model (IPM) used by the U.S. Environmental Protection Agency; the National Energy Modeling System (NEMS) employed by the U.S. Energy Information Administration to develop its Annual Energy Outlook (AEO); the Regional Energy Deployment System (ReEDS), developed by the National Renewable Energy Laboratory (NREL) and the United States Regional Economy, Greenhouse Gas, and Energy (US-REGEN) model, developed by The Electric Power Research Institute (EPRI). Regarding temporal resolution, the US-REGEN model is the most advanced, which is capable of simulating approximately 100 time snapshots per year.[3] Furthermore, none of these tools consider the discrete character of unit-commitment decisions or uncertainty in the models input parameters.

On an international level, the TIMES model, used by the International Energy Agency, allows the user to define the number of time snapshots within a simulated year freely [34,35]. However, typical applications employ 1–12 time snapshots to achieve manageable computation times [1]. The model does not consider detailed operational flexibility of individual power plants (i.e. unit-commitment constraints) or uncertainty in input parameters.

In Chile, the Ministry of Energy develops a long-term energy planning exercise (PELP, due to its acronym in Spanish) every 5 years [36]. This exercise determines several generation expansion scenarios that are later used as an input for the transmission infrastructure expansion planning also developed by the regulator. The model utilized to determine these expansion scenarios is called Power Electricity Timetable (PET), which considers a 30 year planning horizon, with 8 annual time snapshots. In line with previously mentioned models, PET does not include modeling of unit-commitment constraints or uncertainty in input parameters.

In the light of the current practices and in line with the state of the art, we argue that increasing modeling resolution and overall

[1] In this article, variable renewables are understood as wind and solar PV technologies.

[2] A time snapshot (or time slice) refers to a specific operating point of the power system (i.e. a given value of system demand) usually utilized to represent several hours of system operation that are similar among them. Hence, a year can be represented by 1 snapshot (lowest level of resolution), 8,760 snapshots (highest level of resolution if demand and generation data is hourly), or any intermediate value.

[3] The other models consider 17 or less time snapshots.

complexity in planning studies is paramount to appropriately assess and capture the value of energy storage. Hence, this paper provides a systematic assessment of the value of energy storage, in particular of pumped storage hydro capacity in Chile, by using 6 planning optimization models with various levels of complexity. We demonstrate that current policy and regulatory practices may significantly underestimate the value of storage and therefore the need for storage capacity to effectively integrate increased volumes of renewable generation. Failing to appropriately upgrade models may lead to a significant underestimation of VRE integration costs and risks, misleading relevant decisions in policy, regulation, market design and incentives that are necessary to foster synergic technologies needed to complement VRE in investment portfolios.

3. Methodology

3.1. Generation and energy storage expansion planning models

3.1.1. General description

The aim of this section is to present the optimization models, used later on to assess the value of energy storage in energy planning problems, while accounting for various levels of modeling detail. For this purpose, six linear programming models are proposed in order to determine the optimum portfolio of generation and energy storage technologies as modeling complexity is gradually increased. The models minimize total costs (i.e. generation and energy storage investment and operation costs) in a target year, by determining the installed capacities of generation and energy storage plants, subject to several constraints that take into account technical characteristics of system operation and features of the electricity market, such as electricity demand, variable renewable energy availability, maximum/minimum power output of units, operating reserves requirements,[4] CO_2 taxation, storage constraints, among others. Additionally, some of the models (i.e. the most advanced ones) consider several fossil fuel prices scenarios in order to account for uncertainty in these parameters. All models contain two stages,[5] where installed capacities of generation and energy storage plants are decided in the first stage, and overall system operation is determined in a second stage as illustrated in Fig. 1. An increment in modeling detail or complexity is understood here as an augmentation in the set of input parameters and/or mathematical constraints in models, so as to reduce the level of approximation of the model and consider more features of the real system.

Models utilized for the value assessment of storage plants are described below, where modeling complexity is gradually increased (from Model 1 to Model 6; features are accumulative meaning that Model N contains, at least, all features of Model N-1).

Model 1 – "No variability": This corresponds to the simplest optimization model, where the whole target year's electricity demand is compressed into a single time snapshot that represents the estimated average electricity consumption. Apart from neglecting fluctuations in load, no variability is considered for renewable generation outputs, which are thus modelled through a constant availability value. In other words, this model will identify those investment options that can produce energy at the least cost, neglecting all details and complexities in system operation.

Model 2 – "Three monthly time snapshots": We augment modeling complexity in the second model by incorporating three time snapshots/periods per month (so a year is represented through $3 \times 12 = 36$ snapshots), which are used to model the time variability of the load and renewable generation. In particular, a month is represented through a single "average day" which, in turn, is divided in 3 time snapshots that represent night, daylight and evening hours. In this model, solar power availability can only be different to zero in the snapshot that represents daylight hours.

Model 3 – "Hourly variability": The third model incorporates hourly variability of demand and renewable resources, modeling a year through 8,760 h.[6] Here, the load, availability of solar, wind and run-of-river resources and hydro reservoir inflows are modelled through hourly profiles as proposed by Ref. [21].

Model 4 – "Hourly variability with unit-commitment constraints": So far, modeling detail has been augmented by increasing time granularity in the load and renewable resources availability profiles. The fourth model additionally incorporates unit-commitment constraints like those in Ref. [21], which represent technical restrictions of generating units, such as their minimum power output and ramp rate constraints of thermal and hydro plants.

Also, security requirements typically present in power system operations are considered. Specifically, an N-1 reliability criterion is included, which requires that operating reserves must be at least equal to the rated power of the largest unit in the system. Reserves are also held to deal with uncertainty in variable renewable generation and load forecasts as indicated in Ref. [21].

Model 5 – "Stochastic with fuel prices scenarios": The above models are deterministic, in the sense that the number of scenarios considered for the realization of fuel prices is only one. Thus, the fifth model incorporates uncertainty underlying in fossil fuel prices forecasts by considering ten different scenarios. Hence, in this case, expected investment and operation costs are minimized. This is similar to the model proposed in Ref. [21], however in this case, we have included energy storage technologies.

Model 6 – "CVaR constrained model": This is the most complex model, where the conditional value-at-risk (CVaR)[7] of investment and operation costs is constrained, in order to determine generation portfolios that are more robust when facing uncertainty.

When several future fossil fuel prices scenarios are considered in the modeling framework, system investment and operating costs consequently become probabilistic, as explained in Ref. [21]. In this context, the 5%-CVaR of generating portfolio costs is equal to the average investment and operating costs under scenarios equal to or exceeding the 95th percentile of the cost probability distribution. Thus, CVaR constraints added to the model allow the energy planner to establish an upper bound to the average cost under these adverse scenarios and to find a generation mix that would exhibit reduced cost volatility, typically at the expense of higher expected cost.

Table 1 provides a summary of the abovementioned models and Appendix A indicates the detailed mathematical formulation of each model. Summing up, the first three aforementioned models are composed by equations (A.1)-(A.15) shown in Appendix A, each including increasing detail in input parameters. Moreover, the fourth and fifth models utilized are composed by the same set of equations with the additional consideration of system security and unit-commitment constraints (A.16)-(A.39). The main difference between these two models is the consideration of fossil fuel price scenarios in the latter. Finally, the

[4] Operating reserve is the capacity headroom that is left idle or unused, so as to respond to unforeseen conditions during system operation in real time.

[5] Following usual nomenclature in the field of mathematical programming, we use the terms "two-stage" or "two stages" in this paper referring to an optimization program that optimizes decisions in the following two stages: planning stage (i.e. investment decisions) and operational stage (i.e. generation dispatch and reserve decisions). Note that these decisions (in both stages) are, indeed, optimized together. The formulation of the two-stage generation planning problem is presented as one monolithic formulation in the Appendix A.

[6] To speed up calculations, a subset of hours can be selected in order not to affect the final results and reduce computational burden. Through various experiments, we have estimated (for our case studies) that a subset of 2,016 suffices to obtain accurate results.

[7] The α-CVaR is defined as the total cost that is expected in the higher $(1 - \alpha)$% of the cases.

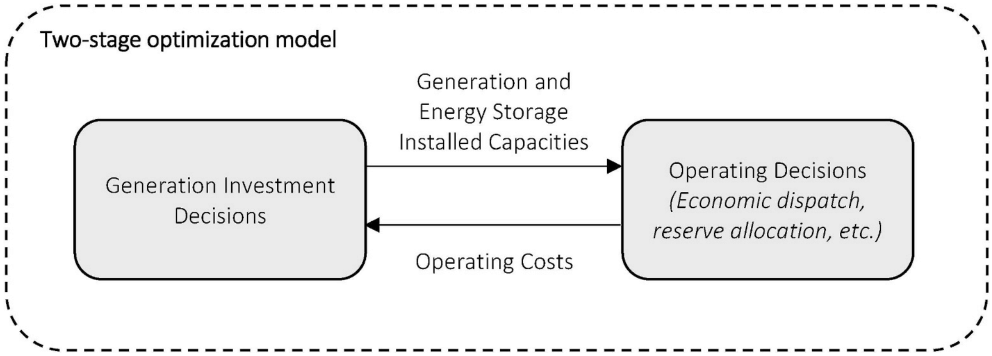

Fig. 1. Investment and operating decisions within the two-stage optimization model framework used in this study.

Table 1
Characteristics of optimization models.

Model	Total number of time snapshots	Sets of Constraints Included in the Model (see Appendix A)	Constraints Included in the Model (see Appendix A)
Model 1 – No variability	1	- Supply-demand balance constraint - Generation capacity constraints - Storage modeling constraints	A.1 – A.15
Model 2 – Three monthly time snapshots	36	- Supply-demand balance constraint - Generation capacity constraints - Storage modeling constraints	A.1 – A.15
Model 3 – Hourly Variability	8,760	- Supply-demand balance constraint - Generation capacity constraints - Storage modeling constraints	A.1 – A.15
Model 4 - Hourly Variability with unit-commitment constraints	8,760	- Supply-demand balance constraint - Generation capacity constraints - Storage modeling constraints - Unit-commitment constraints - System security constraints	A.1 – A.39
Model 5 – Stochastic with fuel prices scenarios	8,760 × 10 scenarios	- Supply-demand balance constraint - Generation capacity constraints - Storage modeling constraints - Unit-commitment constraints - System security constraints	A.1 – A.39
Model 6 – CVaR constrained model	8,760 × 10 scenarios	- Supply-demand balance constraint - Generation capacity constraints - Storage modeling constraints - Unit-commitment constraints - System security constraints - CVaR constraints	A.1 – A.41

sixth model includes Equations (A.40)-(A.41) (or conditional value-at-risk constraints) so risk-constrained generation portfolios can be determined, as proposed by Ref. [21].

3.2. Input data and modeling set-up

We seek to model the Chilean main power system, *Sistema Interconectado Nacional* (SIN), and we select pumped storage hydro as the storage technology to study. Importantly, as we model greenfield investment (i.e. ignoring existing capacity), our focus is to illustrate the main and fundamental differences among the various modeling approaches rather than providing realistic results, centering our analysis on how modeling approaches and approximations may significantly undervalue the impact of energy storage technologies in electricity markets. Table 2 shows the set of available technologies and parameters common to all models. The values used are those employed by the Chilean National Energy Commission (NEC) in recent studies [37,38]. In addition, we use a 10% discount rate to compute annuity values based on investment costs.

A 25 $/ton$CO_2$ CO_2 taxation was set, as assumed by the Chilean Ministry of Energy [39] for the target year, which is 2030.

Additionally, we have set upper bounds for conventional hydroelectric power[8] equal to the current installed capacities in Chile. The values used are 3,393 MW for hydro reservoir and 3,252[9] MW for run-of-river, and these are taken from NEC's studies of the generation market [40]. These assumptions are in line with the most recent planning study performed by the Ministry of Energy [36], where no new hydro reservoir plants were considered and only a reduced amount of new run-of-river plants were installed by the target year (approximately 100 MW in the most optimistic case).

Hydro reservoir technology is modelled as in Ref. [21], taking average parameters of existing power plants in Chile. Lower and upper bounds of water stored in the reservoir were set at 1,556 hm^3 and 10,321 hm^3 respectively. Also, an average inflow-to-power rate of 1.936 $MW/m^3/s$ was assumed.

Roundtrip efficiency for pumped storage hydro (PSH) was set at 75%, which is in line with average values for this type of power plants. Also, a reservoir capacity equivalent to 12 h generation at rated power (i.e. the maximum volume of energy in MWh that can be stored is equal to 12 times the installed capacity in MW) and a minimum volume of

[8] Here we refer as conventional hydro power to hydro reservoir and run-of-river technologies.

[9] This limit includes current small-hydro capacity installed in Chile.

Table 2
Technologies input data common to all models.

	Investment Cost [$/kW]	Operational Cost [$/MWh]	Lifespan [years]	CO_2 Emission Coefficient [tonCO_2/MWh]	Standard Unit's Maximum Output [MW]
Coal	3000	33	35	0.95	170
LNG	1090	88	25	0.44	190
Oil	666	219	25	0.78	25
Solar PV	1200	0	25	0	N/A
Wind	1800	0	35	0	N/A
Run-of-river	4050	0	45	0	50
Hydro reservoir	3500	0	45	0	400
Pumped storage hydro	1283	0	30	0	400

For the stochastic case studies, where we use different fuel prices for a single technology depending on the scenario, this table shows the average value per technology across all 10 scenarios.

stored water equal to zero were assumed.

The demand profile was taken from 2017's real demand and then escalated to fit the Ministry of Energy's projection for the target year, which is 137 TWh [39]. In order to keep calculation times low, we used a representative week for each month. However, operating costs are escalated in order to emulate an entire year of operation.

Although total demand is equal in all six models, its time resolution differs in each one. The first model considers one time snapshot of 15.6 GW with no variability, which represents the average hourly load compressed in a single time period. The second model considers that a month is represented through a single "average day" which, in turn, is reduced to 3 snapshots that represent night, daylight and evening hours. The first (00:00 to 06:00) is a low demand snapshot, the second (07:00-17:00) is a medium demand snapshot and the third (18:00-23:00) is a high demand snapshot, modeling peak hours. Fig. 2 shows the maximum, average and minimum load of each time snapshot across 12 months.

Models 3 to 6 consider an hourly modeling of the load, with a maximum value of 18.3 GW. Fig. 3 shows the consumption of each hour of the day for the target year, illustrating how volatile demand values can be at different hours.

Solar and wind profiles were taken from resource assessment tools developed by University of Chile [41,42], which are widely used by governmental and private institutions. This data was processed in the same way as the load, according to each model characteristics. In Model 1, for instance, variable renewables (solar PV and wind) and conventional hydro average availabilities were set constant at 30% and 50%, respectively. In contrast, solar PV generation is restricted to the second time snapshot in Model 2 (since this snapshot corresponds to daylight hours). Furthermore, for Models 3 to 6, the availability of variable renewable technologies is modelled through hourly profiles. For this purpose, several profiles across various locations in the SIN were taken and then spatially averaged, considering each location's resource potential relative weight and thus generating profiles that are representative of the whole system.

Additionally, we clustered generation units according to their respective technology, as described in 7.2, so as to make the computational process more efficient. In Table 3, input parameters for unit-commitment and system security constraints, such as maximum ramp rates, minimum output and spinning reserve costs are shown. The values used are taken from the Chilean Independent System Operator [43]. Note that for completeness, we show detailed demand, variable renewable resources and conventional hydro resource profiles in Appendix B.

Also, spinning reserve requirements are set to 3% of the hourly load and 5% of each hour's variable renewable generation, as proposed by Ref. [44]. In line with Table 2, the rated capacity of the largest unit in the system is 400 MW, which is used to establish an N-1 criterion for system reserves.

As mentioned in section 3.1, the fifth and sixth models consider several fossil fuel prices scenarios. These scenarios were obtained as in Ref. [21] and their main characteristics (prices and probabilities) are shown in Fig. 4. Fig. 4 (a) shows prices for all fuel types and scenarios considered in models, ordered according to overall cost. Fig. 4 (b) on the other hand, shows the probability of each scenario, revealing the log-normal shape of the distribution obtained by assuming random-walk processes on fuel prices returns as explained in detail in Ref. [21]. Note that we have laid out fossil fuel price scenarios data in table form

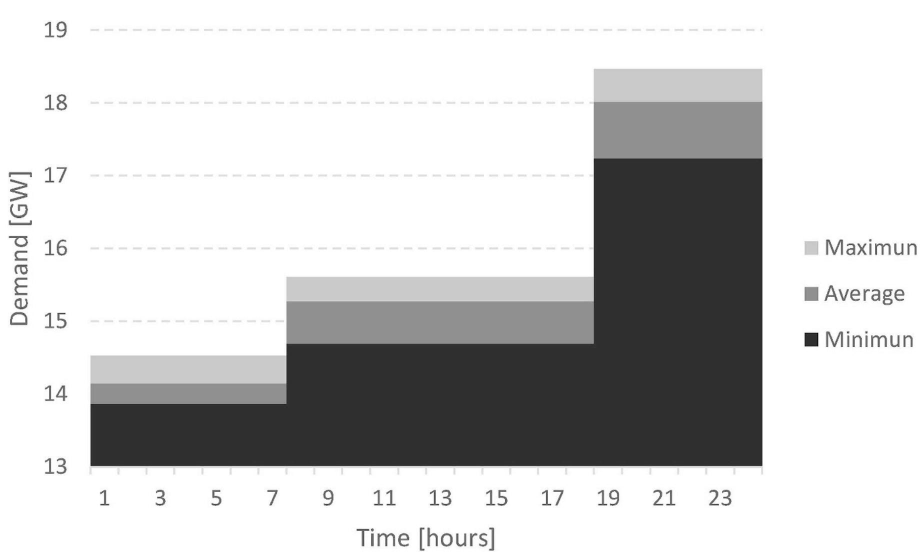

Fig. 2. Three time snapshots demand modeling.

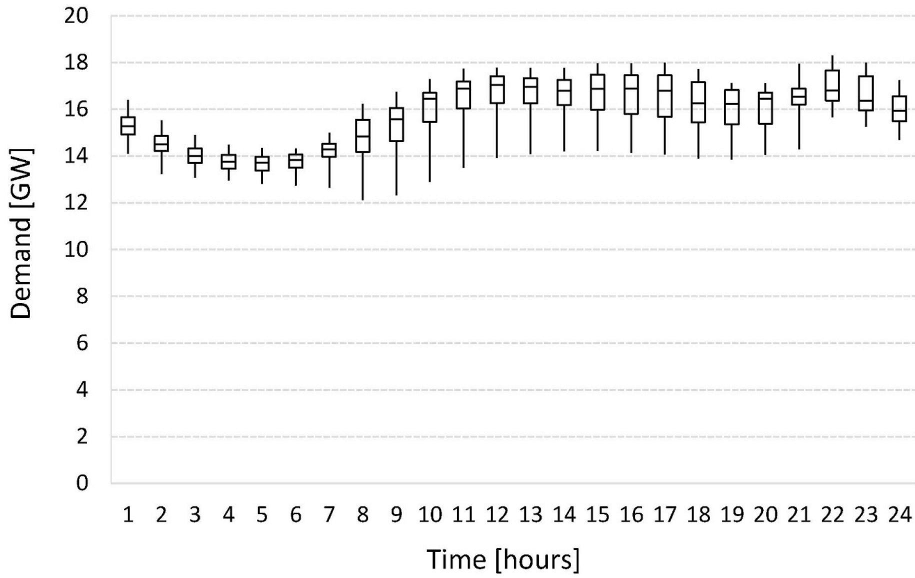

Fig. 3. Statistics of hourly load in the target year.

Table 3
Unit-commitment parameters common to Models 4 to 6.

	Spinning Reserve Cost [$/MW/h]	Minimum Output [MW]	Maximum Upward/ Downward Ramp Rate [MW/min]
Coal	3.3	85	2
LNG	8.8	76	11
Oil	21.9	4	10
Solar PV	0	0	–
Wind	0	0	–
Run-of-river	0	25	50
Hydro reservoir	0	200	50
Pumped storage hydro	0	0	50

in Appendix B.

Finally, Model 6 considers an α parameter of 0.95, which defines scenarios contributing to CVaR.

4. Results and discussion

We divide results and their respective analysis in seven sections below, one for each of the 6 models, and a final analysis that draws conclusions on tendencies identified across all cases.

Table 4
Optimal generation portfolio and generation (as a percentage of total demand) of Model 1.

	Installed Capacity [GW]	Generation [%]
Coal	0.00	0
LNG	0.00	0
Oil	0.00	0
Solar PV	41.00	78.7
Wind	0.00	0
Run-of-river	3.25	10.4
Hydro reservoir	3.39	10.9
Pumped storage hydro	0.00	0
Total Investment and Operation Cost	5420 [MM$]	

MM$ refers to million dollars.

4.1. Model 1 – "no variability"

Table 4 shows the generation portfolio determined by Model 1, which consists mostly on conventional hydro and solar PV capacity. Imposed bounds on hydropower capacity are binding, since these technologies present an efficient balance between capacity factor and investment costs. Moreover, as solar PV generation is considered always available (since Model 1 only considers a single time snapshot) and

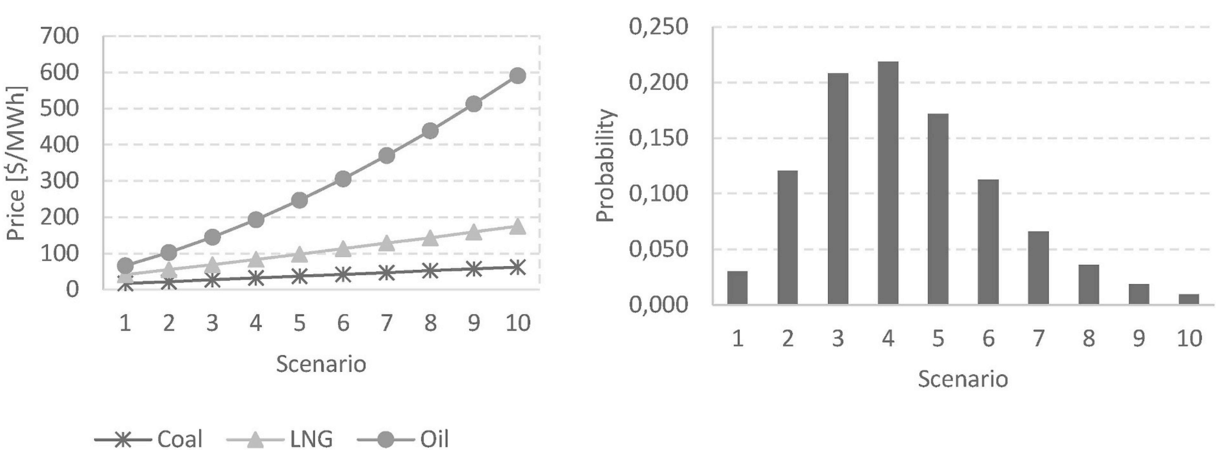

Fig. 4. (a) Fossil fuel prices scenarios. (b) Probability of each scenario.

Table 5
Optimal generation portfolio and generation (as a percentage of total demand) of Model 2.

	Installed Capacity [GW]	Generation [%]
Coal	0.00	0
LNG	0.00	0
Oil	0.00	0
Solar PV	4.38	7.9
Wind	36.95	70.6
Run-of-river	3.25	10.4
Hydro reservoir	3.39	10.8
Pumped storage hydro	0.24	0.3
Total Investment and Operation Cost	8423 [MM$]	

Table 6
Optimal generation portfolio and generation (as a percentage of total demand) of Model 3.

	Installed Capacity [GW]	Generation [%]
Coal	2.15	9.8
LNG	1.17	1.2
Oil	0.19	0.03
Solar PV	23.53	38.7
Wind	13.30	21.2
Run-of-river	3.25	8.9
Hydro reservoir	3.39	9.2
Pumped storage hydro	7.24	10.9
Total Investment and Operation Cost	8839 [MM$]	

presents a relatively high load factor (30%) and low investment costs, this technology is the most economical alternative to expand generation capacity beyond hydropower capacity (which is assumed to be limited).

As shown in Table 4, pumped storage hydro has zero economic value in this setting. As no variability is modelled for demand, wind, solar generation, etc.; and there is no consideration of technical constraints that could rise flexibility requirements in the system, storage is simply not economically efficient in this simplistic model.

4.2. Model 2 – "three monthly time snapshots"

In the second model, we have introduced load and variable renewable variabilities through the addition of three time snapshots per month. Due to this new modeling feature, results in Table 5 show that a mix of generation and energy storage technologies is needed to efficiently produce the required electricity demand throughout the year. In this case, both solar PV and wind power plants are used to serve the load, accompanied by pumped storage hydro capacity. For validation purposes, another instance of this model was run, forcing installed capacity of PSH to be zero. The latter resulted in 39 GWh of variable renewable generation curtailment over the target year, demonstrating the value of energy storage to allow integration of higher volumes of renewables in an efficient manner.

It is important to emphasize that the abovementioned curtailments of renewable generation were observed even when the full capacity of hydro reservoir generation was installed by the model (i.e. installed capacity of hydro reservoir generation resulted equal to the predefined upper bound, which reflects the current level of installed capacity of hydro reservoir generation in Chile). This is important since there is a belief that actual installed capacity levels of hydro reservoir generation in Chile (without further support from PHS) can effectively support integration of higher levels of renewables, which is disproven by our results. In fact, although water can be stored during the day in hydro reservoirs (while PV generation supplies the load) and used during the night to produce electrical energy, hydro reservoir plants cannot withdraw (pump) and store surpluses of electrical energy available in the electricity system. PHS, instead, can effectively do so, presenting a clear advantage over traditional hydro plants.

4.3. Model 3 – "hourly variability"

As stated above, in the third model we incorporate hourly time resolution in the load, variable renewables and conventional hydro inflow profiles. These new features drastically change the results, as shown in Table 6. In this case, the generation portfolio is composed by all available technologies, including a significant increase in pumped storage hydro capacity.

Variability in model input parameters makes variable renewable generation insufficient to economically serve the load throughout all hours. Hence, dispatchable thermal units and energy storage are incorporated in the portfolio. Results in Table 6 show that the optimal generation portfolio is composed by 3.5 GW of thermal capacity, mainly LNG and coal-fired units. Since this model does not consider technical system constraints or security requirements, these technologies are triggered solely by the need of complementing variable renewable generation. Moreover, PSH optimal installed capacity increases 7 GW if compared to Model 2 results.

Fig. 5 shows system operation during a 24-h period. In this graph, the difference between demand and total generation represents PSH's pumping electricity consumption (i.e. stored energy plus losses, the latter due to a roundtrip efficiency equal to 75%). High variable renewable generation between 8:00-19:00 implies a generation surplus that is stored in PSH units and then used for covering electricity load at night (see Fig. 6 for a detailed illustration of PSH operation).

Fig. 5 corresponds to a winter day, when demand is more intensive and solar energy availability is the lowest, as is the case in Chile. Thus, during this season, storage of solar power is insufficient to cover night-time load, consequently requiring LNG generation at night. In summer, solar surplus combined with energy storage is sufficient to cover the total demand, hence LNG plants are left unused during that season. LNG plants are thus mainly used as backup generation for higher demand periods.

4.4. Model 4 – "hourly variability with unit-commitment constraints"

Unit-commitment and system security constraints added to this model, include technical constraints of the operation of generation units and reserve requirements. Specifically, ramping up/down limits, minimum power output and spinning reserve requirements were considered in the model. These constraints increase the cost of accommodating variable renewable generation in the operation of the system, since these technologies augment reserve requirements and may require other units to act as a back-up for dealing with their variable feature. Table 7 supports the previous hypothesis, since solar PV and wind generation are reduced when considering these new constraints.

The need for flexibility in the system also increments the value of pumped storage hydro, which exhibits greater installed capacity when compared to the previous results.

Fig. 7 and Fig. 8 show system operation for the same day as that in Fig. 5. The main difference in this case, is that thermal generation is present throughout all hours, in contrast with the operation shown in the previous section (see hour 11 in both figures).

Technologies holding reserve during the same day are shown in Fig. 9 and Fig. 10. Here it can be seen that coal-fired units are holding reserve during the 11th hour, consequently affecting system operation as described in the previous paragraph. In the rest of the hours, PSH and hydro reservoir play an important role in system security. Since these technologies act as peaking units, they typically generate more intensively during peak hours, leaving idle capacity for holding reserve during the remaining time. An overall summary of the allocation of reserves is shown in Table 8, which shows the importance of PSH and hydro reservoir power in this context. Both technologies provide almost

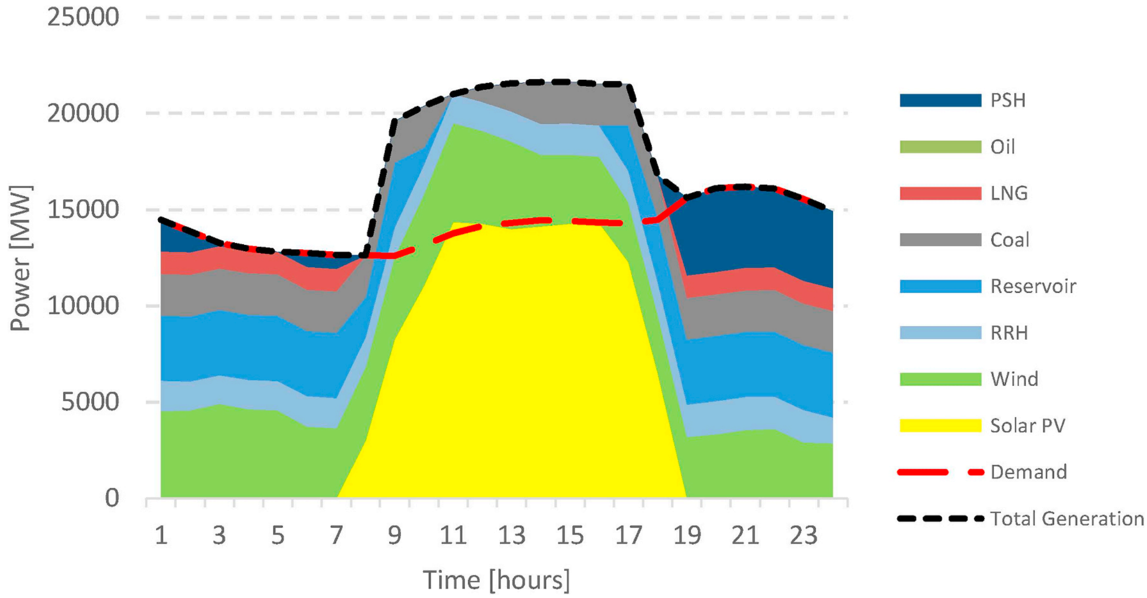

Fig. 5. 24-h operation of the system (winter day), obtained using Model 3.

97% of the yearly reserve requirement.

4.5. Model 5 – "stochastic with fuel prices scenarios"

In this model, fuel prices scenarios are incorporated, hence, the investment decision should allow for the minimization of installing and expected operating costs.

Results are shown in Table 9. Installed capacities do not differ substantially with previous results. Moreover, here we present statistical parameters of the costs under different scenarios: conditional value-at-risk (i.e. the expected installing and operating cost of scenarios exceeding 95th percentile) and standard deviation, which we will use as a measure of volatility or risk.

4.6. Model 6 – "CVaR constrained model"

By incorporating CVaR constraints, we can limit risk exposure of the generation portfolio. This should change the composition of the optimal mix, as concluded in Ref. [21].

Table 7
Optimal generation portfolio and generation (as a percentage of total demand) of Model 4.

	Installed Capacity [GW]	Generation [%]
Coal	2.56	11.7
LNG	1.08	0.9
Oil	0.00	0
Solar PV	23.41	38.5
Wind	12.46	20.0
Run-of-river	3.25	8.8
Hydro reservoir	3.39	9.3
Pumped storage hydro	7.83	10.9
Total Investment and Operation Cost	8937 [MM$]	

Table 10 shows that a 9082 MM$ CVaR was obtained, which is 338 MM$ less than the amount obtained in Model 5 (while also increasing expected costs in 127 MM$). Additionally, standard deviation of scenario costs (or risk) is reduced in this case, decreasing from

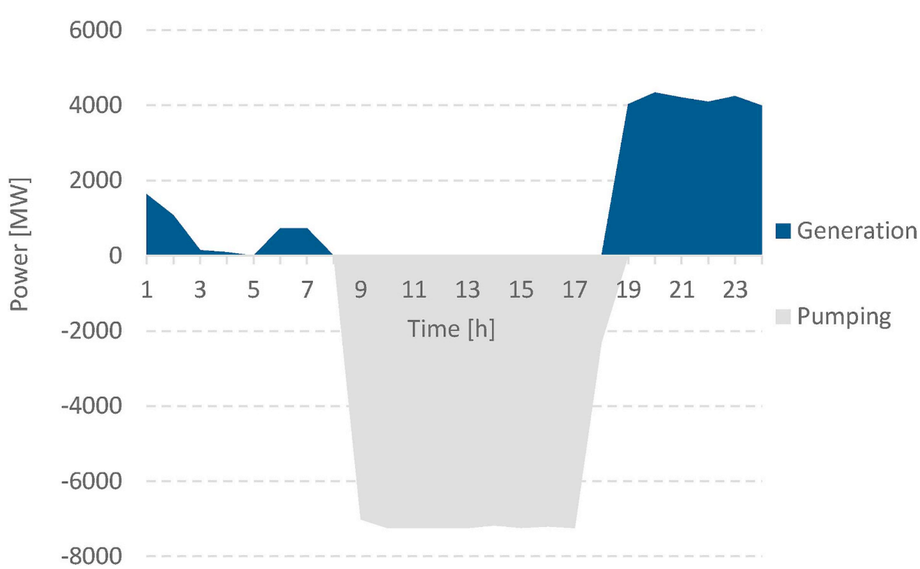

Fig. 6. Operation of pumped storage technology in winter day depicted in Fig. 5.

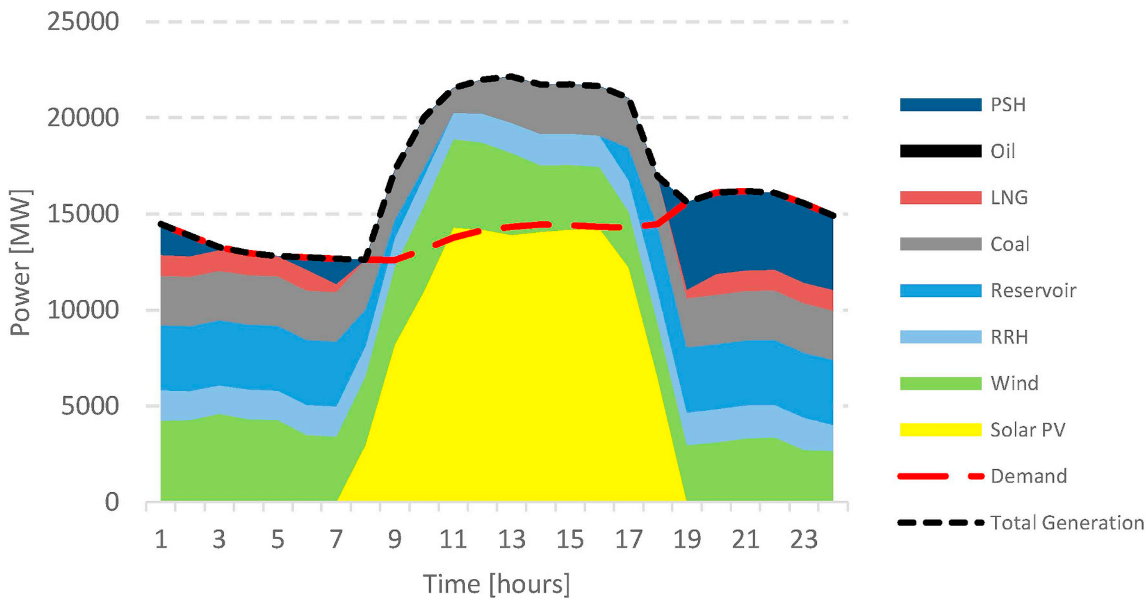

Fig. 7. 24-h operation of the system (winter day), simulated using Model 4.

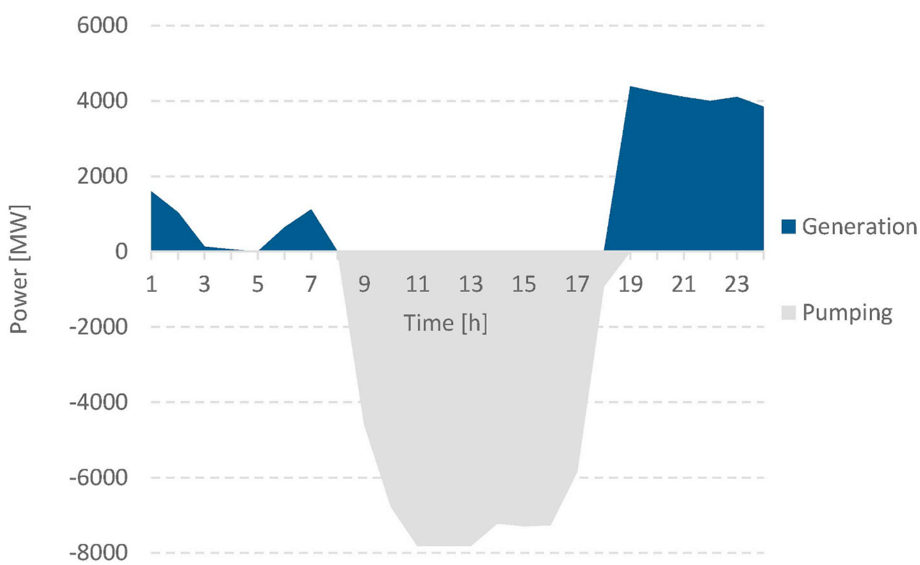

Fig. 8. Operation of pumped storage technology in winter day depicted in Fig. 7.

245 MM$ in Model 5 to 7 MM$ in Model 6. Hence, risk is reduced at the expense of higher expected costs.

Here, thermal generation is significantly displaced by renewable contributions, including approximately 38% less investment on thermal technologies and an increase of 21% investment on variable renewable plants and this is in line with our previous findings in Ref. [21]. Moreover, the generation mix exhibits 79% of expected generation from variable renewable technologies in the target year (whereas Model 5 portfolio presented 67%). The latter is justified since renewable generation is independent from fuel price volatility, hence these technologies are more competitive relative to their thermal counterparts in high prices scenarios.

The thermal portfolio in this case is only composed by LNG power plants. As high variable renewable capacity is installed, utilization of thermal plants is relegated to providing reserve and operating as back-up, hence the capacity factor of these technologies is low (nearly 7% in all scenarios). The combination between installing and operating costs in the highest fuel price scenarios, together with this low utilization, makes LNG the preferred technology[10].

A novel result here is the increase in optimal storage capacity when limiting CVaR. At first glance, one hypothesis to explain this effect could be that renewables are deployed for decreasing portfolio risk, hence the value of energy storage increases as a complement for these technologies. Nevertheless, by running both Model 5 and Model 6 and fixing variable renewable capacity at 0 MW, we also found increasing amounts of energy storage when limiting CVaR (617 MW versus 387 MW). Hence, we conclude that operating flexibility provided by energy storage, can also be used to deliver robustness for facing risk

[10] This was corroborated by calculating the optimal generation mix for all scenarios contributing to the CVaR, individually. All these calculations resulted in LNG plants as the preferred thermal technology. Also, given its low utilization, this technology presents the lowest Levelized Cost of Electricity (LCOE) among all three thermal technologies, under each of the scenarios contributing to the CVaR.

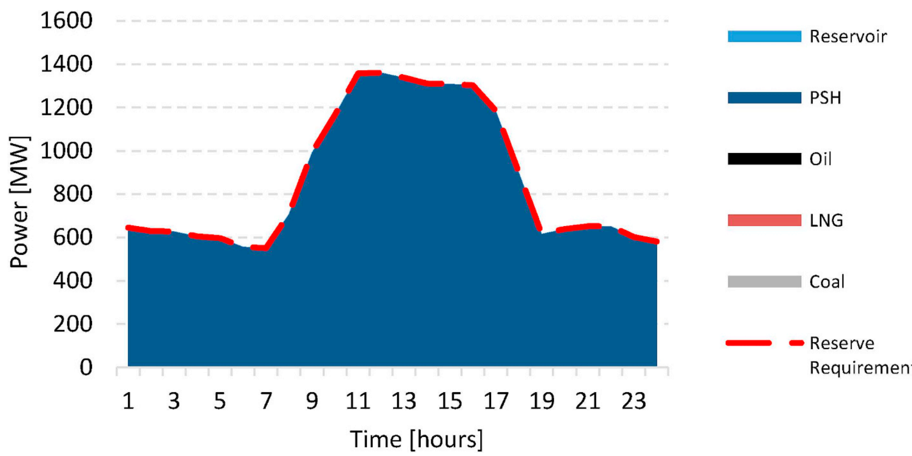

Fig. 9. Optimal upward spinning reserve allocation.

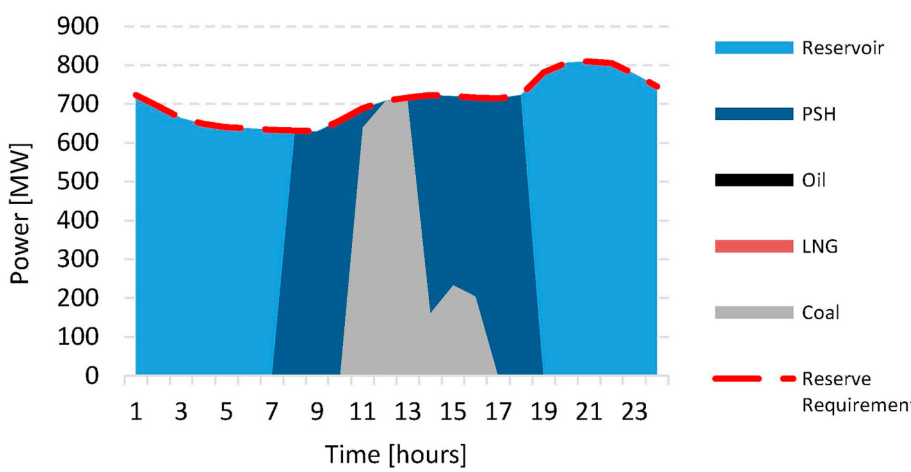

Fig. 10. Optimal downward spinning reserve allocation.

against uncertain fuel prices in the planning time-scales, since the technology is capable of reducing cost in adverse scenarios, even in the absence of variable renewable generation.[11]

4.7. Comparison and discussion

Table 11 shows the optimal generation portfolio for each model and Fig. 11 presents the economic value of energy storage in each solution (i.e. the difference between expected installing and operating costs with and without energy storage). Results show that increasing modeling complexity directly impacts both investment in energy storage and its economic value.

Accounting for the hourly variability of the load and renewable resources availabilities produces the greatest change in PSH investment (an order of magnitude higher when full time resolution is recognized in the planning model) among all the complexity increments. However, this feature negatively impacts variable renewables optimal installed capacities. This can be concluded from results obtained in Models 1 to 3.

Unit-commitment constraints and scenario modeling both justify higher PSH investment due to the necessity of flexibility in the operation of the power system. Energy storage also contributes to risk minimization against uncertain fuel prices which is a novel result. Moreover, risk is also minimized through renewable energy investment which confirms previous studies [21].

Interestingly, and in line with the previous comment, the largest change in the value of storage is due to the risk constraint (from Model 5 to 6). In effect, if planners are more risk averse, storage technologies will present an increasing value to make larger amounts of renewables feasible. Furthermore, without energy storage, the integration of renewables to mitigate long-term risks will be more costly and even infeasible, making investments in storage technologies more attractive.

Table 8
Spinning reserve allocation by technology.

	Upward Spinning Reserve [%]	Downward Spinning Reserve [%]	Overall Spinning Reserve [%]
Coal	0.03	5.87	2.59
LNG	0.06	0	0.03
Oil	0	0	0
Hydro reservoir	8.33	32.17	18.77
Pumped storage hydro	91.61	61.95	78.63

[11] In line with our results, others authors have found that nuclear power plants might provide similar risk-mitigating benefits as energy storage, given the technology's relative low variable cost risk (both in the presence and absence of variable renewable generation) [45,46]. To our knowledge, no study has analyzed possible synergies or competing effects of nuclear power plants and energy storage under a cost-risk optimization framework, and this is proposed for future research.

Table 9
Optimal generation portfolio, generation (as a percentage of total demand) and planning cost by scenario of Model 5.

	Installed Capacity [GW]	Expected Generation [%]
Coal	2.46	11
LNG	1.09	1
Oil	0.03	0.01
Solar PV	23.36	38.1
Wind	12.79	20.4
Run-of-river	3.25	8.8
Hydro reservoir	3.39	9.2
Pumped storage hydro	7.84	10.6
Expected Investment and Operation Cost	8862 [MM$]	
CVaR	9420 [MM$]	
Standard Deviation	245 [MM$]	

Table 10
Optimal generation portfolio, generation (as a percentage of total demand) and planning cost by scenario of Model 6.

	Installed Capacity [GW]	Expected Generation [%]
Coal	0.00	0
LNG	2.22	1.3
Oil	0.00	0
Solar PV	22.07	35
Wind	21.66	35
Run-of-river	3.25	8.9
Hydro reservoir	3.39	9.3
Pumped storage hydro	8.16	10.2
Expected Investment and Operation Cost	8989 [MM$]	
CVaR	9082 [MM$]	
Standard Deviation	7 [MM$]	

Table 11
Optimal generation portfolio of each model.

	Installed Capacity					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	[GW]	[GW]	[GW]	[GW]	[GW]	[GW]
Coal	0.00	0.00	2.15	2.56	2.46	0.00
LNG	0.00	0.00	1.17	1.08	1.09	2.22
Oil	0.00	0.00	0.19	0.00	0.03	0.00
Solar PV	41.00	4.38	23.53	23.41	23.36	22.07
Wind	0.00	36.95	13.30	12.46	12.79	21.66
Run-of-river	3.25	3.25	3.25	3.25	3.25	3.25
Hydro reservoir	3.39	3.39	3.39	3.39	3.39	3.39
Pumped storage hydro	0.00	0.24	7.24	7.83	7.84	8.16

5. Conclusions

By running six long-term energy planning models of the Chilean electricity generation sector, we obtain generation portfolios with an increasing amount of energy storage (i.e. pumped storage hydro) installed capacity, due to the consideration of higher levels of modeling complexity.

Particularly, results show that augmenting time resolution increases the economic value of energy storage. For instance, higher time resolution allows the planning models to capture those hours when availability of renewable resources do not coincide with demand peaks, hence requiring back-up generation that is provided by thermal and energy storage plants. In our particular case study, the increase in economic value of storage, due to a higher time resolution recognized in the planning model, escalates the overall installed capacity of PSH by an order of magnitude, from 0.2 GW in Model 2 to 7.2 GW in Model 3. Evidently, the installed capacity of storage plants resulting from Model 1 is the lowest (and equal to 0 MW) since it neglects the temporal resolution of the investment problem, necessary to recognize the value of storage.

Furthermore, considering operational flexibility of power plants in planning models (i.e. minimum power output and ramp rate constraints of thermal and hydro plants) and system security constraints (i.e. operating reserves requirements) further increases the resulting economic value of energy storage and, consequently, its optimal installed capacity, increasing, in our case study, installed capacity of storage plants from 7.2 GW (Model 3) to 7.8 GW (Model 4 and 5). PSH technology, in this case, is the preferred technology for holding operating reserves, due to its idle generating capacity (and stored energy) during off-peak hours. Furthermore, we find that reducing the risk exposure of the generation portfolio by incorporating CVaR constraints in the model, also increases energy storage value and its resulting installed capacity, increasing, in our case, installed capacity of storage plants from 7.8 GW (Model 5) to 8.1 GW (Model 6). Results show that even in the absence of VRE generation, energy storage helps reducing electricity generation costs in high fossil fuel prices scenarios, hence decreasing electricity cost risk.

In the light of these results, it is clearer that increasing modeling resolution and overall complexity in planning studies is paramount to appropriately assess the value of energy storage. This is so because of the ability of energy storage technologies to support a more flexible and secure operation of the electricity system, which implies that models should be able to capture the value of storage in providing such flexibility and security services in order to determine the optimal capacity requirements in an electricity system. Failing to do so may lead to a significant underestimation of VRE integration costs and the economic value of energy storage.

Moreover, conclusions drawn in our study may be of use by energy planners seeking ways to reduce the effects of volatile fuel prices in the generation sector, since our analyses show that energy storage technologies may help reduce electricity cost risk in the planning timescale.

Acknowledgements

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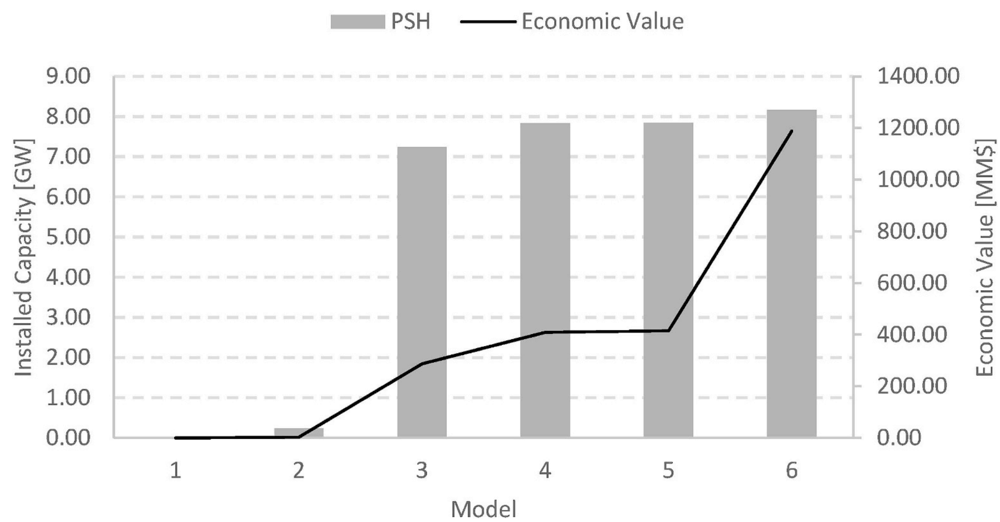

Fig. 11. Installed capacity and economic value of energy storage in each model.

Appendix A. Mathematical Appendix

Nomenclature

Sets

I	Set of generation technologies
I^H	Set of conventional hydro technologies, (hydro technologies with exception of pumped storage hydro)
I^R	Set of variable renewable energy technologies
I^T	Set of thermal technologies
S	Set of scenarios
T	Set of time snapshots in the simulated year

Parameters

Dem_t	Electricity demand in time snapshot *t*. [MWh]
d_i	Storage capacity of pumped storage hydro (PSH) and hydro reservoir technologies in hours, defined as the maximum time it can sustain its rated output without pumping. [hours]
EC_i	CO_2 emission coefficient of technology *i*. [tCO_2eq/MWh]
$\mathrm{FU}_{i,s}$	Fuel cost of technology *i* in scenario *s*. [$/MWh]
inf_t	Water inflow of hydro reservoir technology in time snapshot *t* per unit of installed capacity. [hm^3/MW]
INV_i	Annuitized investment cost of technology *i* (this includes yearly fixed maintenance costs). [$/MW-year]
K	Maximum conditional value-at-risk (CVaR) of generation portfolio costs. [$]
$\mathrm{p_s}$	Probability of occurrence of scenario *s*. [p.u.]
$\overline{\mathrm{P}}_i$, $\underline{\mathrm{P}}_i$:	Maximum and minimum power output of each unit of technology *i*. [MW]
$\mathrm{P}^{\mathrm{R}}_{i,t}$	Normalized generation availability of variable renewable or run-of-river technology *i* at time snapshot *t*. [p.u.]
$\mathrm{R}_i^{\mathrm{UP,DN}}$	Ramp rate limits of technology *i*. [MW/h]
RU_i	Spinning reserve cost of technology *i*. [$/MW/h]
$\underline{\mathrm{V}}_i$, $\overline{\mathrm{V}}_i$	Normalized upper and lower bounds of stored water in PSH and hydro reservoir technologies.[12] [hm^3/MW]
VOLL	Value of lost (or curtailed) load. [$/MWh]
α	CVaR parameter that defines the $(1-\alpha)$% highest cost scenarios. [p.u.]
δ^{D}	Fraction of hourly demand held as spinning reserve. [%]
δ^{R}	Fraction of hourly variable renewable generation held as spinning reserve. [%]
$\Delta\mathrm{P}$	Rated power of the largest unit in the system. [MW]
η	Electrical energy generated by utilizing 1 hm^3 of stored water in hydro reservoir technology. [MWh/hm^3]
τ	CO_2 tax. [$/$tCO_2eq$]
ϕ^-	Electrical energy generated by utilizing 1 hm^3 of water in PSH technology. [MWh/hm^3]
ϕ^+	Electrical energy consumed when pumping 1 hm^3 of water onto PSH technology's reservoir. [MWh/hm^3]

Decision Variables

cap_i	Installed capacity of technology *i*. [MW]
C_s	Total investment and operating costs in scenario *s*. [$]
d_s	α – CVaR auxiliary variable that represents the right deviation of the cost in scenario *s* with respect to the value of variable z. [$]

[12] The upper bound parameter should be calculated consistently with assumed storage hours of each technology (d_i).

$DS_{i,t,s}$ Downward spinning reserve of the technology i in time snapshot t under scenario s. [MWh]
$\overline{DS}_{i,t,s}^{1/2}$ Auxiliary variable that limits the available downward spinning reserve due to capacity (1) or energy (2) limitations in technology i. [MWh]
$E_{i,t,s}$ Energy stored in technology i in time snapshot t under scenario s. [MWh]
E_i Energy storage capacity of technology i. [MWh]
$G_{i,t,s}$ Generation of technology i in time snapshot t under scenario s. [MWh]
$G_{PSH,t,s}^{+}$ Pumping energy consumption of PSH technology in time snapshot t under scenarios s. [MWh]
$G_{PSH,t,s}^{-}$ Generated energy of PSH technology in time snapshot t under scenario s. [MWh]
$LL_{t,s}$ Curtailed load in time snapshot t under scenario s. [MWh]
$N_{i,t,s}$ Number of on-line units of technology i in time snapshot t under scenario s
$US_{i,t,s}$ Upward spinning reserve of technology i in time snapshot t under scenario s. [MWh]
$\overline{US}_{i,t,s}^{1/2}$ Auxiliary variable that limits the available upward spinning reserve due to capacity (1) or energy (2) limitations in technology i. [MWh]
$V_{i,t,s}$ Water stored in technology i in time snapshot t under scenario s. [hm^3]
$\lambda_{t,s}$ Spillage of water in time snapshot t under scenarios s. [hm^3]
z α – CVaR (auxiliary) variable that represents the value-at-risk of investment and operation costs. [$]

Abbreviations

Hydro reservoir RES
Pumped storage hydro PSH
Run-of-river RRH

Optimization model

The formulation presented here considers the highest level of modeling detail employed in the study (as in the case of Model 6). This is sufficient since the rest of the models used are composed by a sub-set of the constraints described in the present section. Nevertheless, we divide the formulation in several sets of equations, in order to explicitly identify which constraints are considered in each model (as in Table 1).

The two-stage stochastic optimization model minimizes overall expected investment and operating cost of generation and storage technologies considering several fossil fuel price scenarios within a monolithic formulation. Investment costs are modelled through the annuitized value of capital cost of technologies per unit of capacity. Operating costs, on the other hand, include fuel costs, operation and maintenance costs (the latter included in the INV_i parameter), social costs of CO_2 emissions and spinning reserve costs.[13]

$$\text{O.F. :min} \sum_{s \in S} \mathrm{p}_s \cdot C_s \tag{A.1}$$

s.t.:

$$C_s = \sum_{i \in I} \text{INV}_i \cdot cap_i + \sum_{i \in I} \sum_{t \in T} (\text{FU}_{i,s} + \text{EC}_\text{i} \cdot \tau) \cdot G_{i,t,s} + \sum_{i \in I^T} \sum_{t \in T} US_{i,t,s} \cdot \text{RU}_\text{i} + \sum_{t \in T} \text{VOLL} \cdot LL_{t,s} \qquad \forall\ s\ \in S \tag{A.2}$$

Supply-demand balance constraints

Equation (A.3) balances electricity supply and demand throughout all simulated time snapshots. This constraint imposes that demand and PSH pumping consumption should match generated power and curtailed load at all times.

$$\sum_{i \in I \setminus \{PSH\}} G_{i,t,s} + G_{PSH,t,s}^{-} = \text{Dem}_t - LL_{t,s} + G_{PSH,t,s}^{+} \qquad \forall\ t \in T, \forall\ s \in S \tag{A.3}$$

Generation capacity constraints

Equation (A.4) sets the upper bound of generation output according to each technology's installed capacity and (A.5) links each technology's output to the number of on-line units:

$$N_{i,t,s} \cdot \overline{\text{P}}_\text{i} \leq cap_i \qquad \forall\ s \in S, \forall\ t \in T, \forall\ i \in I \setminus \{I^R\} \tag{A.4}$$

$$G_{i,t,s} \leq N_{i,t,s} \cdot \overline{\text{P}}_\text{i} \qquad \forall\ s \in S, \forall\ t \in T, \forall\ i \in I \tag{A.5}$$

Availabilities of variable renewable and run-of-river technologies are modelled through normalized profiles as imposed by Equation (A.6):

$$G_{i,t,s} \leq \text{P}_{\text{i,t}}^{\text{R}} \cdot cap_i \qquad \forall\ s \in S, \forall\ t \in T, \forall\ i \in I^R \tag{A.6}$$

Reservoir modeling constraints

Technologies with storage capability, such as hydro reservoir and PSH, were modelled by assuming a single representative reservoir for each technology, as in Ref. [21]. For both technologies, reservoir maximum and minimum levels[14] rise as the installed capacity of the technology grows, so as to account for the consequent increase in system storage capacity when new units are built, as proposed by Ref. [21]. Additionally, a decision variable to account for possible spillage was included in the case of hydro reservoir.

Thus, Equations (A.7)-(A.13) model the variation of stored water levels and impose upper and lower bounds for these variables. Equations relating stored volumes of water and stored energy are not strictly necessary for now, although they will become relevant when system security

[13] These costs arise due to the loss of efficiency while operating thermal units below their rated power. We model this effect by considering a constant reserve cost in $/MWh.
[14] Inflows are also considered to grow proportionally to installed capacity in the case of hydro reservoir technology.

constraints are introduced.

$$V_{PSH,t,s} = V_{PSH,t-1,s} - \frac{G^{-}_{PSH,t,s}}{\phi^{-}} + \frac{G^{+}_{PSH,t,s}}{\phi^{+}} \quad \forall\, s \in S, \forall\, t \in T \tag{A.7}$$

$$V_{RES,t,s} = V_{RES,t-1,s} - \frac{G_{RES,t,s}}{\eta} + \mathrm{inf}_t \cdot cap_{RES} - \lambda_{t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.8}$$

$$V_{i,t,s} \leq cap_i \cdot \bar{\mathrm{V}}_i \quad \forall\, s \in S, \forall\, t \in T, \forall\, i \in \{RES, PSH\} \tag{A.9}$$

$$cap_i \cdot \underline{V}_i \leq V_{i,t,s} \quad \forall\, s \in S, \forall\, t \in T, \forall\, i \in \{RES, PSH\} \tag{A.10}$$

$$E_{PSH,t,s} = V_{PSH,t,s} \cdot \phi^{-} \quad \forall\, s \in S, \forall\, t \in T \tag{A.11}$$

$$E_{RES,t,s} = V_{RES,t,s} \cdot \eta \quad \forall\, s \in S, \forall\, t \in T \tag{A.12}$$

$$E_i = cap_i \cdot \mathrm{d}_i \quad \forall\, i \in \{RES, PSH\} \tag{A.13}$$

Maximum pumping and generating power of PSH technology are determined by the maximum consumption/output of on-line units, as shown in Equations (A.14) and (A.15).

$$G^{+}_{PSH,t,s} \leq N_{PSH,t,s} \cdot \bar{\mathrm{P}}_{PSH} \quad \forall\, s \in S, \forall\, t \in T \tag{A.14}$$

$$G^{-}_{PSH,t,s} \leq N_{PSH,t,s} \cdot \bar{\mathrm{P}}_{PSH} \quad \forall\, s \in S, \forall\, t \in T \tag{A.15}$$

Unit-commitment constraints

Equation (A.16) sets the lower bound of generation according to each technology's number of on-line units:

$$N_{i,t,s} \cdot \underline{\mathrm{P}}_{\mathrm{i}} \leq G_{i,t,s} \quad \forall\, s \in S, \forall\, t \in T, \forall\, i \in I \tag{A.16}$$

Equations (A.17-A.18) set an upper bound for each technology's change in output through time, according to the number of online units and the maximum ramp rate parameter ($\mathrm{R}_{\mathrm{i}}^{\mathrm{UP,DN}}$) [21]:

$$G_{i,t,s} - G_{i,t-1,s} \leq \min\{N_{i,t,s}; N_{i,t-1,s}\} \cdot \mathrm{R}_{\mathrm{i}}^{\mathrm{UP}} + (N_{i,t,s} - N_{i,t-1,s}) \cdot \underline{P}_i \quad \forall\, s \in S, \forall\, t \in T, \forall\, i \in I \backslash \{I^R\} \tag{A.17}$$

$$G_{i,t-1,s} - G_{i,t,s} \leq \min\{N_{i,t,s}; N_{i,t-1,s}\} \cdot \mathrm{R}_{\mathrm{i}}^{\mathrm{DN}} + (N_{i,t-1,s} - N_{i,t,s}) \cdot \underline{P}_i \quad \forall\, s \in S, \forall\, t \in T, \forall\, i \in I \backslash \{I^R\} \tag{A.18}$$

System security constraints

Operating reserve requirements are also included in the model. Equation (A.19) imposes that a minimum amount of spinning upward reserve (i.e. unused power capacity available for rapid deployment when facing a contingency, such as the disconnection of a generation unit), equal to the largest unit in the system, should be held at all times (i.e. N-1 criterion for security of supply). Furthermore, reserves also account for demand and variable renewable generation availability uncertainties. For this purpose, Equations (A.20-A.21) impose spinning reserve requirements equal to a fraction of demand and variable renewable generation, as proposed by Ref. [44]:

$$\sum_{i \in I} US_{i,t,s} \geq \Delta \mathrm{P} \quad \forall\, s \in S, \forall\, t \in T \tag{A.19}$$

$$\sum_{i \in I} DS_{i,t,s} \geq \delta^{\mathrm{D}} \cdot \mathrm{Dem}_{\mathrm{t}} \quad \forall\, s \in S, \forall\, t \in T \tag{A.20}$$

$$\sum_{i \in I} US_{i,t,s} \geq \delta^{\mathrm{R}} \cdot \sum_{i \in I^R} G_{i,t,s} + \delta^{\mathrm{D}} \cdot \mathrm{Dem}_{\mathrm{t}} \quad \forall\, s \in S, \forall\, t \in T \tag{A.21}$$

Equation (A.22) and Equation (A.23) link upward and downward spinning reserves to each thermal technology's minimum, maximum and scheduled power outputs:

$$US_{i,t,s} \leq N_{i,t,s} \cdot \overline{\mathrm{P}_{\mathrm{i}}} - G_{i,t,s} \quad \forall\, s \in S, \forall\, t \in T, \forall\, i \in I^T \tag{A.22}$$

$$DS_{i,t,s} \leq G_{i,t,s} - N_{i,t,s} \cdot \underline{P_i} \quad \forall\, s \in S, \forall\, t \in T, \forall\, i \in I^T \tag{A.23}$$

Moreover, Equations (A.24)-(A.31) limit the amount of spinning reserve that can be held in PSH technology, according to the maximum, minimum and scheduled output of units. Also, as stored energy can also limit the amount of reserve, Equations (A.25) and (A.29) model this effect.

$$\overline{US}^{1}_{PSH,t,s} \leq N_{PSH,t,s} \cdot \bar{\mathrm{P}}_{PSH} - G^{-}_{PSH,t,s} + G^{+}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.24}$$

$$\overline{US}^{2}_{PSH,t,s} \leq E_{PSH,t,s} - G^{-}_{PSH,t,s} + G^{+}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.25}$$

$$US_{PSH,t,s} \leq \overline{US}^{1}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.26}$$

$$US_{PSH,t,s} \leq \overline{US}^{2}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.27}$$

$$\overline{DS}^{1}_{PSH,t,s} \leq N_{PSH,t,s} \cdot \bar{\mathrm{P}}_{PSH} + G^{-}_{PSH,t,s} - G^{+}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.28}$$

$$\overline{DS}^{2}_{PSH,t,s} \leq (E_{PSH} - E_{PSH,t,s}) + G^{-}_{PSH,t,s} - G^{+}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.29}$$

$$DS_{PSH,t,s} \le \overline{DS}^{1}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.30}$$

$$DS_{PSH,t,s} \le \overline{DS}^{2}_{PSH,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.31}$$

Similarly, Equations (A.32)-(A.39) model upward and downward spinning reserve of hydro reservoir technology.

$$\overline{US}^{1}_{RES,t,s} \le N_{RES,t,s}\cdot \bar{P}_{RES} - G_{RES,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.32}$$

$$\overline{US}^{2}_{RES,t,s} \le E_{RES,t,s} - G_{RES,t,s} + \inf_{t}\cdot cap_{RES}\cdot \eta \quad \forall\, s \in S, \forall\, t \in T \tag{A.33}$$

$$US_{RES,t,s} \le \overline{US}^{1}_{RES,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.34}$$

$$US_{RES,t,s} \le \overline{US}^{2}_{RES,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.35}$$

$$\overline{DS}^{1}_{RES,t,s} \le N_{RES,t,s}\cdot \underline{P}_{RES} + G_{RES,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.36}$$

$$\overline{DS}^{2}_{RES,t,s} \le (E_{RES} - E_{RES,t,s}) + G_{RES,t,s} - \inf_{t}\cdot cap_{RES}\cdot \eta \quad \forall\, s \in S, \forall\, t \in T \tag{A.37}$$

$$DS_{RES,t,s} \le \overline{DS}^{1}_{RES,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.38}$$

$$DS_{RES,t,s} \le \overline{DS}^{2}_{RES,t,s} \quad \forall\, s \in S, \forall\, t \in T \tag{A.39}$$

Conditional value-at-risk constraints

Finally, conditional value-at-risk is constrained in the model through equations (A.40) and (A.41) as in Ref. [21]. This set of equations impose that the average investment and operation costs of the (1−α)% most costly scenarios is restrained from exceeding the K parameter.

$$d_s \ge C_s - z \qquad \forall\, s\, \in S \tag{A.40}$$

$$z + \frac{1}{1-\alpha}\sum_{s\,\in\, S} d_s\cdot p_s \le \mathrm{K} \tag{A.41}$$

Appendix B. Additional Data

Additional data has been made available in the spreadsheet at the URL: https://bit.ly/2QGj7PP

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