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A new solution to mitigate hydropeaking? Batteries versus re-regulation reservoirs

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ABSTRACT

Hydropower plants frequently operate at high output during peak hours and at low output (or even shutoff) during off-peak hours. This scheme, called "hydropeaking", is harmful to downstream ecosystems. Operational constraints (minimum flows, maximum ramps) are frequently used to mitigate the impacts of hydropeaking. However, they reduce the operational flexibility of hydroelectric dams and increase the operational cost of power systems. Another approach to mitigating ecological impacts from hydropeaking is using structural measures, such as re-regulation reservoirs or afterbays. The first contribution of our work is to study the cost-effectiveness of these re-regulation reservoirs in mitigating ecological impacts from subdaily hydropeaking. Our second contribution is assessing energy storage (specifically, batteries) to mitigate the financial impacts of implementing peaking restrictions on dams, which represents the first attempt in the literature. Understanding these mitigation options is relevant for new hydropower dams, as well as for existing ones undergoing relicensing processes. For this, we formulate an hourly mixed-integer linear optimization model to simulate the annual operation of a power system. We then compare the business-as-usual (unconstrained) hydropower operations with ecologically constrained operations. The constrained operation, by limiting hydropower ramping rates, showed to obtain flows close to the natural streamflow regime. As next step, we show how re-regulation reservoirs and batteries can help to achieve these ecological constraints at lower costs. While the former are cost-effective for a very broad range of investment costs, the latter will be cost-effective for hydropeaking mitigation from 2025 onwards, when their capital costs have fallen. If more stringent environmental constraints are imposed, both solutions become significantly more attractive. The same holds for scenarios of more renewable generation (in which the operational flexibility from both alternatives becomes more valuable). After 2030, batteries can match the cost-effectiveness of expensive re-regulation reservoirs. Our findings are valuable for policy and decision makers in energy and ecosystem conservation.

1. Introduction

Hydropeaking refers to an operational scheme of a hydropower plant, in which the plant operates at high capacity during high-value, "peak" hours and at low capacity (or even shutoff) during low-value, "off-peak" hours. This practice results in highly fluctuating downstream flows. Although river flows have a natural variation, fluctuations at the subdaily scale caused by hydropower plants are far more severe and impact the downstream river ecosystems (Dibble et al., 2015; Yin et al., 2018). Fish populations face degradation of habitat and increased mortality due to stranding caused by a rapid fluctuation of the water level (Scruton et al., 2003). Benthic populations face the risk of drifting due to high differences in water velocities (Cristina Bruno et al., 2010). Riparian plants face both physiological and physical constraints because of the shifts between submergence and drainage, and erosion of substrates (Bejarano et al., 2018). There are further physical

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Nomenclature of the model

Sets

g	Power plants
t	Time
ta	Alias index for time steps

Variables

$P_{g,t}$	MWh, Generated energy by plant g at time step t
P_t^{uns}	MWh, Unserved energy at time step t
P_t^{cur}	MWh Curtailed energy from the grid at time t
P_t^{char}	MWh, Energy stored into BESS (charging) at time step t
P_t^{disc}	MWh, Energy supplied by BESS (discharging) at time step t
Q_t^{out}	m^3/s, Outflow to the river at time step t
Q_t^{spill}	m^3/s, Spilled flow at time step t
Q_t^{turb}	m^3/s, Turbine flow at time step t
$B_{g,t}$	-, Plant on/off (binary variable)
RB_t	-, Richard-Baker flashiness index at time step t
$RampNeg_t$	(m^3/s)/h, Down ramping rate at time step t
$RampPos_t$	(m^3/s)/h, Up ramping rate at time step t
SoC_t	%, Battery state of charge at time step t
R_t	m^3, Re-regulation reservoir stored volume at time step t
V_t	m^3, Reservoir stored volume at time t
MIT	$, Resulting annuity cost of mitigation option

Inputs

c^g	$/MWh, Variable generation cost of plant g
c^{uns}	$/MWh, Penalty for unserved energy
D_t	MW, Demand at time step t
P_t^{max}, P_t^{min}	MW, Maximum power output of plant g
Q_t^{in}	m3/s. Natural inflow into the reservoir
$R^{min}R^{max}$	m3/s, Minimum/maximum volume of the re-regulation reservoir
V^{min}, V^{max}	m3/s, Minimum/maximum volume of the reservoir
c^{BE}	$/MWh, Cost of battery energy capacity
c^{BP}	$/MW, Cost of battery power capacity
Δt	s, Time step size
C	MWh, Rated battery energy capacity
DoD	%, Maximum battery depth of discharge
η	%, Battery charging/discharging efficiency
MIF	m3/s, Environmental minimum flow
MRR	(m^3/s)/h, Maximum ramping rate
N	MW/(m^3/s), Hydropower plant yield
$tMin^{on}$	h, Minimum online time of coal power plant

stressors caused by hydropeaking, such as temperature anomalies (Carpentier et al., 2017) and modification in the sediment dynamics. Altogether, water bodies with extreme fluctuations can lead to reduced populations of macroinvertebrate communities and become fishless (Poff and Zimmerman, 2010). A comprehensive overview of the impacts of hydropeaking on the river ecology is given by Zimmerman et al. (2010).

New power market structures (Kern et al., 2012) and variable renewable systems may exacerbate these impacts (Haas et al., 2015). Since hydropower has distinct operational advantages over other renewable technologies, new installations are projected to increase significantly (Zarfl et al., 2014). This motivates the search for new models and solution methods to tackle complex hydropower systems (Feng et al., 2018) including their multiple purposes (Hu et al., 2014), as well as for cost-effective ways of mitigating the ecological impacts of hydropeaking.

Indicators of Hydrologic Alteration (Richter et al., 1996) and Environmental Flow Components (Mathews and Richter, 2007), among other environmental flow statistics, are approaches often used for quantifying the disruptive ecological effects of dams and other human activities on streamflow patterns. For quantifying the impacts of hydropeaking on streamflow regime, it is necessary to use statistics that apply on higher (hourly) resolutions to capture the *subdaily* hydrologic alteration (Cristina Bruno et al., 2010). Many previous studies used the streamflow "flashiness" index from Richards-Baker (R-B) (Baker et al., 2004) to study impacts related to hydropeaking (Olivares et al., 2015). The R-B flashiness index essentially quantifies hour-to-hour changes in streamflow as a proportion of total flow experienced. Other popular metrics include the number of reversals, percent of total flow (Lundquist and Cayan, 2002), and coefficient of diel variation (McKinney et al., 2001).

In general, the ecological impacts of hydropeaking can be mitigated by introducing operational constraints on dam operators. Examples include maximum ramping rates, which limits hour-to-hour differences in reservoir discharge, and minimum flows (He et al., 2018). But these operational constraints cause dam owners (or power fleet owners) to incur increased operational costs (Guisández et al., 2013) because the peaking capacity of hydropower needs to be replaced by expensive thermal peaking plants such as natural gas or diesel. To avoid or reduce this additional cost, physical mitigation options such as re-regulation reservoirs (RRR) or afterbays downstream of the hydroelectric dam (Richter and Thomas, 2007) can be implemented together with operational restrictions.

The ecologic and economic value of RRR has been explored earlier (Olivares, 2008). Further, RRR have been analyzed for different projects from a technical point of view, including dams converted to pumped-storage hydropower that then essentially operate as batteries (Pérez-Díaz et al., 2012). But, so far, there are no studies about the cost-effectiveness (including investment costs) of RRR as a mitigation alternative.

Another option for mitigating the impacts of hydropeaking is energy storage, such as pumped hydro storage, compressed air energy storage, power to gas (electrolyzers), and batteries (Kousksou et al., 2013). The first two have shown a slow development in recent years (Hart and Sarkissian, 2016). Power to gas is considered to be a promising technology by some regions but still in early stages of deployment (Hart and Sarkissian, 2016). Battery energy storage systems (BESS), however, are rapidly increasing their installation rates and are projected to soon be viable for energy peaking purposes in power systems (Child et al., 2017b). Lower-cost BESS could conceivably substitute for the peaking ability usually provided by conventional hydropower plants, by storing hydropower produced during off-peak hours and discharging this power during peak hours. The market for grid-scale BESS is growing quickly, reaching volumes in 2015 that were four times larger than any prior year (Hart and Sarkissian, 2016). Future projections for the year 2030 indicate (Li-ion BESS) cost reductions of the order of 60%–80% (Breyer et al., 2017). A potential downside of BESS is their (still) limited lifetime. Current stationary BESS come with warranties of about 10,000 cycles but only if the state of charge is controlled adequately. At, say, two cycles per day, this equals to about 13.5 years, standing in great contrast to conventional peaking technologies (and RRR) that last several decades.

Still, BESS are already being implemented in systems to address reliability issues and help incorporate renewables. For example, the largest Li-ion BESS (100 MW) has just been deployed in Australia, and another 50 MW in South Korea (IRENA, 2015), which aims to install 2000 MW of battery storage by 2020. On the other side of the globe, California has a new bill requesting 1300 MW of storage power capacity by 2024 (Legislative Counsel, 2010) to support its transition to a fully renewable system. The attractiveness of BESS investments is growing through shared-economy models; here a peak-shaving application of BESS has shown to achieve financial returns above 30% per year (Lombardi and Schwabe, 2017). From a grid operator's point of view, grid-scale BESS has proven to significantly decrease operational costs (Goebel et al., 2017). Also for industrial applications, large-scale BESS can be deployed cost-effectively, for example in mining operations (Pamparana et al., 2017). More generally on storage technologies, two recent publications systemized modeling approaches for investment planning with storage (Haas et al., 2017) and the need for storage in highly renewable power systems (Cebulla et al., 2018). Together, the two publications looked at over 100 studies. These and many other studies focus on the viability of BESS for improving economic and reliability outcomes in power systems. However, none of them has addressed how BESS can potentially reduce human pressure on sensitive freshwater ecosystems below dams.

The novelty of our work lies in comparing the cost-effectiveness of RRR and BESS in mitigating (subdaily) hydrologic alteration downstream of hydropower plants. Specifically, the questions to be answered are:

i) Cost-effectiveness: What is the techno-economic performance of RRR and BESS in mitigating the hydrologic alteration caused by a hydropower plant?
ii) Selection: Which alternative is better? When do we pick an alternative over the other?

To answer these questions, we designed a case study. There, we explored increasing shares of renewable generation, different stringencies of environmental constraints, hydrologic years, and a wide range of investment costs of RRR and BESS.

The results of this work have important implications for how exogenous changes in grid technology in coming decades could alter the use of hydroelectric dams and make it more feasible to reduce the impacts of dams on downstream ecosystems. This is relevant for both new hydro dams and for relicensing of existing ones. For example, in South America and in Chile, massive amounts of solar energy projects are forecasted; for their integration, the existing hydropower park could buffer the day-night cycle but not without exacerbating the hydrologic alteration (Haas et al., 2018b, 2015). Globally, developing regions project over 700 GW of new hydropower dams in the next 20 years (Zarfl et al., 2014), whereas developed countries more commonly face relicensing processes of existing operations. For example, in the U.S. alone, 35 GW of hydropower plants need to renew their license before 2030 (Federal Energy Regulatory Commission, 2018). All these situations will require a careful assessment of how to cope with hydropeaking to protect the ecology of their water bodies.

The work is organized into five sections. The methods and model are described in Section 2. The case study is detailed in Section 3, with results discussed in Section 4. Finally, conclusions and future work are presented in Section 5.

2. Methods and electricity model

We study a system in which new environmental regulations impose strict maximum ramping rates (MRR) that limit variations in streamflow downstream of the hydroelectric dam. To reduce the resulting system costs (arising from the lower flexibility), an RRR and a BESS are added to the system. We will examine, i) whether RRR and BESS are efficient in reducing those over-costs (while complying with the environmental constraints), and ii) under which conditions one alternative is better than the other.

Power system and market operations are represented here using a hydrothermal dispatch model, such as can be found in the literature (Olivares et al., 2015). The particularity of our model is that it explicitly models RRR and BESS, under the imposition of environmental constraints. The model uses mixed integer linear programming (MILP) to minimize the operational costs (mainly fuel) on an hourly resolution for a 1-year simulation period (8760 time steps).

The model is designed to run in 4 distinct modes, one for each of the three mitigation alternatives (a gray area of Fig. 1-a) plus the base case:

1) Business as usual (BAU), where the dam operator is functionally unconstrained;
2) Operational constraints;
3) RRR (together with the operational constraints); and
4) BESS (together with the operational constraints).

Business-as-usual is used as a benchmark for measuring the cost increase in the other options. Under the operational constraints, the dam operator is obligated to meet the environmental constraint (MRR) only by altering the reservoir release pattern. In theory, this is where the overall system should suffer the highest increase in operational costs. In the RRR alternative, an RRR is built downstream of the dam, and therefore the MRR constraint is imposed on its releases (but not strictly on the releases of the upstream hydropower plant). And lastly, when deploying BESS, MRR is imposed on the reservoir releases again, while the batteries assist in "shifting" power production by storing hydropower during low-value hours and releasing it during high-value hours. The corresponding equations for each mitigation alternative are also shown in Fig. 1-a.

We apply our tool to a hypothetical case study composed of hydropower reservoirs, coal-fired, diesel-fired, solar photovoltaic, and (onshore) wind power plants, as illustrated in Fig. 1-a. We test our findings for different scenarios of water flows; different shares of renewable technologies in the power system; and varying degrees of stringency in the constraints on hydropeaking (MRR). We also test a broad range of investment cost inputs for the RRR and BESS.

In the remainder of the section, we will explain the electricity model (Fig. 1-a), including the modeling of the hydropeaking mitigation options (gray area Fig. 1-a). In section 3, we will show the relevant inputs of the case study, starting in section 3.1 with the hydrologic scenarios (Fig. 1-b) and the generation mix scenarios (Fig. 1- c). Then in section 3.2, we will detail the studied MRR values (Fig. 1- d) and the investment costs of the mitigation options (Fig. 1-e). In section 3.3 we will then explain the procedure of the cost-benefit analysis (Fig. 1-f).

2.1. Objective function

The objective function of the hydrothermal dispatch model is to minimize the total operational cost Z of the system (shown in eq. (1)). For this, the model allocates values to both binary and continuous decision variables controlling the "on/off" status and amount of generation $P_{g,t}$ of each power plant. The first term from the left is the operational cost of generation from the power plants (fuel costs and variable operation and maintenance cost c_g). The

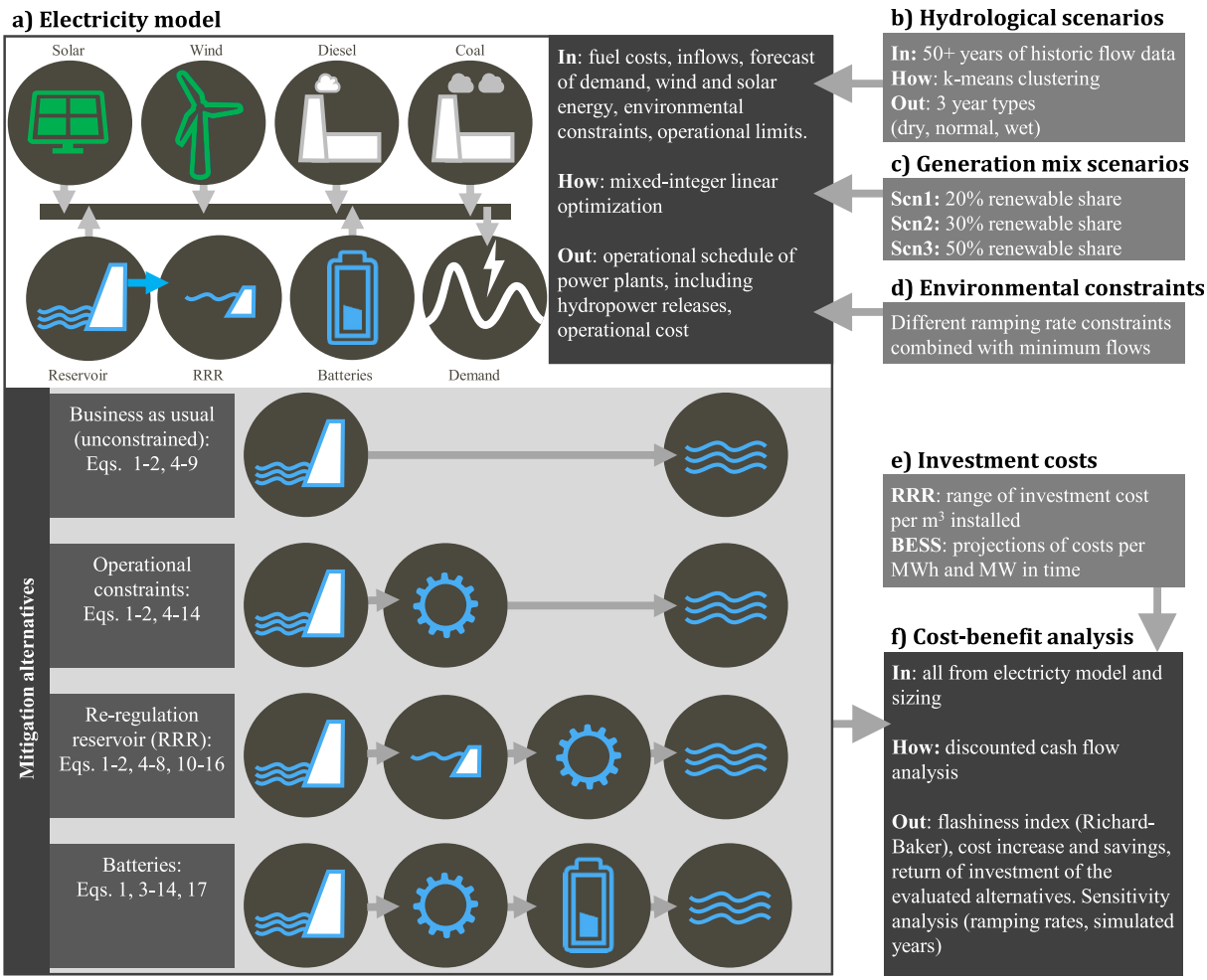

Fig. 1. Framework of the study. Each box refers to a segment of this study, detailing the inputs and outputs. a) Electricity model with the different mitigation options. b) Three hydrological years as inputs to the electricity model. c) Three generation mix scenarios with growing renewable shares. d) Ramping rates (combined with minimum flows). e) Different investment costs of RRR and BESS. f) Cost-benefit analysis.

second term is the penalty c_{uns} for unserved energy P_t^{uns}.

$$Min\ Z = \sum_{t,g}^{T,\ G} c_g P_{g,t} \Delta t + \sum_{t}^{T} c_{uns} P_t^{uns} \Delta t,\ \ \forall t, g \tag{1}$$

2.2. Energy balance

Our model uses a uni-nodal energy balance (i.e. no transmission constraints), where the generation plus the unserved energy needs to meet demand D_t (eq. (2)). In situations of overproduction from renewable technologies, the model has the option to curtail energy P_t^{cur}. For the mitigation option with BESS, the energy flows from and to the batteries (P_t^{disc}, P_t^{char}) need to be considered (eq. (3)).

$$\sum_{g}^{G} P_{g,t} + P_t^{uns} - P_t^{cur} = D_t,\ \ \forall t, g \tag{2}$$

$$\sum_{g}^{G} P_{g,t} + P_t^{uns} - P_t^{cur} + P_t^{disc} - P_t^{char} = D_t,\ \ \forall t, g \tag{3}$$

2.3. Power plants

2.3.1. Technical minimum and maximum power output

The maximum output of each power plant is limited by its installed capacity P_g^{max}. Additionally, if it is on (i.e. $B_{g,t} = 1$), it has to respect its technical minimum $P_g^{\min}$ (eq. (4)).

$$B_{g,t}\, P_g^{min} \le P_{g,t} \le B_{g,t} P_g^{max},\ \ \forall\ t, g\ \varepsilon\ \mathbb{G} \tag{4}$$

2.3.2. Renewable power plants

The wind and solar power plants are considered as inputs to the system. Excess energy can be handled with the variable for energy curtailment P_t^{cur}. The production profiles are hourly and modeled with perfect foresight. Neglecting forecast errors is unfavorable for the investment of storage devices (Moreno et al., 2017), making this a conservative assumption (for the profitability of RRR and BESS).

2.3.3. Thermal power plants

It takes several hours for a coal power plant to start and shut down, therefore minimum online ($tMin_{g,t}^{on}$) and offline times need to be considered. Eq. (5) shows the formulation for the online time. The offline time is analogous. More details on how this is applied can be found in Olivares et al. (2015). Ramping rates of thermal

power plants are not active constraints, given that during an hourly time frame an online coal power plant can move from its minimum to maximum power output. Older coal power plants might be less flexible, which would further increase the value of water. Neglecting this makes our study more conservative in terms of the profitability of mitigation options.

$$\sum_{ta=t}^{t+tMin_{g,t}^{on}-1} B_{g,ta} \geq tMin_{g,t}^{on}(B_{g,t} - B_{g,t-1}), \quad \forall\ t \tag{5}$$

To take into account the reduced efficiency of the coal power plant when operating at partial load, we introduced an additional term to the objective function (but not shown for the sake of simplicity). This inefficiency is viewed as an additional cost to the operation. To keep the model linear, we implemented a piecewise-linear approximation of the efficiency curve.

As for diesel power plants, the above minimum on- and offline time is set to 1 h and can be disregarded for this reason. Further, they are not constrained by ramping rates. Their efficiency is assumed to be constant, which is another assumption that makes our study more conservative for the mitigation alternatives.

2.3.4. Hydropower constraints

Power generation from the hydropower plant is modeled with a constant yield N from turbined water Q_t^{turb} to power P_t^g, which is a common approach in energy planning (eq. (6)). This yield is the product of the hydraulic head, specific density of water, gravity and the efficiency of the turbogeneration units. The stored water V_t is constrained by the volume (V^{min}, V^{max}) of the reservoir in eq. (7). The water balance (eq. (8)) ensures the volume continuity of water. Q_t^{in} is the natural inflow to the hydropower reservoir, Q_t^{turb} the turbined flow, and Q_t^{spill} the spilled flow. In absence of RRR, the flow in the river Q_t^{Out} corresponds to the turbined flow Q_t^{turb} plus the spilled flow Q_t^{spill} (eq. (9)). The water volume at the beginning and end of the simulation horizon is set to half of its maximum capacity.

$$P_t^g = NQ_t^{turb}, \quad \forall\ t \tag{6}$$

$$V^{min} \leq V_t \leq V^{max}, \quad \forall\ t \tag{7}$$

$$(V_t - V_{t-1})/\Delta t = Q_t^{in} - Q_t^{turb} - Q_t^{spill}, \quad \forall\ t \tag{8}$$

$$Q_t^{Out} = Q_t^{turb} + Q_t^{spill} \tag{9}$$

2.4. Mitigation options

2.4.1. Environmental constraints

In this model, we applied two types of environmental constraints (as hard-constraints to the model). The first is minimum flows *MIF* (eq. (10)), meaning that the flow returned to the river always has to be greater or equal than that value. This is a constraint commonly found in hydropower plants. The second constraint is maximum ramping rate *MRR*, which stipulates that the absolute difference between flows Q_t^{out} of two consecutive time steps is below that value. This holds for up- and down-ramping, which is captured in eq. (11) with the use of the absolute value. While we will only use one value for *MIF*, we will subject *MRR* to sensitivities in the case study.

$$Q_t^{Out} \geq MIF, \quad \forall\ t \tag{10}$$

$$\left|Q_t^{Out} - Q_{t-1}^{Out}\right| \leq MRR, \quad \forall\ t \tag{11}$$

To model an absolute value in linear programming, we require further steps. The first step is to include two auxiliary variables for separately accounting for the positive and negative ramps ($RampPos_t$ and $RampNeg_t$). Their sum needs to be below the allowed *MRR* (eq. (12)). Additionally, we define them as positive variables (eq. (13)). Therefore, the difference in the flow returned to the river Q_t^{out} between two consecutive hours is either captured in the variable of positive or negative ramps. For example, if $Q_t^{out} = 110$ and $Q_{t-1}^{out} = 100$, the flow difference is 10 (right hand side of eq. (14)). From the left hand side of eq. (14), it follows that $RampPos_t = 10$ because $RampNeg_t$ can only adopt positive values and will consequently become zero. Finally, eq. (12) would make sure that 10 + 0 is below the allowed MRR.

$$RampPos_t + RampNeg_t \leq MRR, \quad \forall t \tag{12}$$

$$RampPos_t, RampNeg_t \geq 0. \tag{13}$$

$$RampPos_t - RampNeg_t = Q_t^{out} - Q_{t-1}^{out}, \quad \forall t \tag{14}$$

2.4.2. Re-regulation reservoir constraints

The water balance in the RRR (if installed) depends on the plant's turbined flow from upstream Q_t^{turb}, spilled flow from upstream Q_t^{spill}, and its releases Q_t^{RRR} (eq. (15)). The instream flow results directly from the releases of the RRR (eq. (16)). The water level in the RRR at the beginning and end of the simulation horizon is also equal to half of its capacity.

$$\frac{R_t - R_{t-1}}{\Delta t} = Q_t^{turb} + Q_t^{spill} - Q_t^{RRR}, \quad \forall t \tag{15}$$

$$Q_t^{Out} = Q_t^{RRR} \tag{16}$$

Note that Q_t^{RRR} is a decision variable, which means that the operation of the RRR is decided by the optimization model. This implies that the hydropower reservoir can operate more freely, and that the RRR is in charge of determining releases such that the MRR and MIF are met.

2.5. Battery energy storage system

Within the optimization, batteries are modeled in terms of their energy balance and their maximum depth of discharge. Capacity-fade and replacement at the end of their life are considered ex-post in the discounted cash flow analysis.

The energy balance of the BESS depends on the energy charged to and discharged from it (P_t^{char}, P_t^{disc}), corrected by its efficiencies η. The left-hand side of eq. (17) shows the change of state of charge SoC_t of the battery, which is expressed in percentage. Multiplied by its nominal energy capacity C, it gets a dimension of energy (MWh). Due to technical reasons, only a part of the battery's nominal energy capacity can be used, for which we correct by the factor of maximum depth of discharge *DoD*. Fig. 2 clarifies the terms of this energy balance. Further, the batteries are constrained by their installed power capacity and by their installed energy capacity (not shown for the sake of brevity).

$$C \cdot DoD \cdot (SoC_t - SoC_{t-1})/\Delta t = \eta P_t^{char} - P_t^{disc} \Big/ \eta, \ \forall t \tag{17}$$

Analogous to the RRR, the battery's operation (P_t^{char}, P_t^{disc}) is

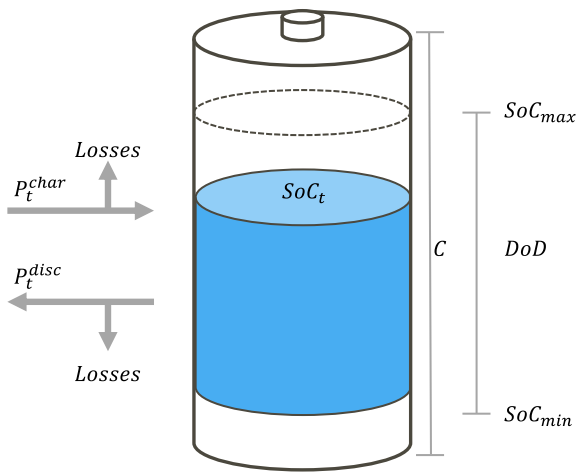

Fig. 2. Energy balance of the battery, adapted from Lombardi and Schwabe (2017).

found by the model. In other words, when the hydropower reservoir has a more limited operation in order to meet the MRR and the MIF, that missing flexibility is provided by the batteries.

3. Case study

3.1. General description and scenarios

In this section, we will detail the inputs of the case study. The considered power system is composed of one of each thermal, hydro, and renewable power plants. We decided to work with a hypothetical test system to reduce computational time; the user-defined installed capacities result in a mix that could roughly resemble central Chile. To take into account the variability of demand (Alvarez et al., 2017), inflows (Haas et al., 2015), and solar and wind power generation (Molina et al., 2017), we used profiles from central Chile (Rapel). Inflows and load profiles correspond to historical data, whereas solar and wind time series are synthetic based on validated models (Department of Geophysics - University of Chile and Ministry of Energy of Chile, 2012a, 2012b). The main model inputs can be found in the supplementary material (Anindito, 2018).

The results of the hydropeaking mitigation alternatives might depend on the power system under study. Therefore, we define three scenarios with growing renewable energy capacity (20%, 30%, 50% in terms of energy with solar and wind in equal parts). All of them have the same hydro, coal, and diesel power capacity. This is done for capturing the current development of renewable deployment and the behavior of the hydropower production (which can show an exacerbated hydropeaking scheme under these conditions (Kern et al., 2014)). The load is assumed to have no growth for ease of comparison. Table 1 shows the resulting dimensions. The mean hydropower generation depends on the considered hydrologic scenarios (see next paragraph), which directly impact the diesel- and coal-based generation. Growing renewable shares also affect the fossil generation (but we verified that the resulting coal power plant achieves an economically feasible capacity factor).

The considered power system is rather small. Therefore, it could be viewed as a fleet of a single power company, an isolated power system, or a sub-system (of a larger power system that for example suffers from transmission bottlenecks). Besides keeping computing times small, using a small power system is motivated by the ease of illustrating the behavior of its different elements and solutions (as opposed to large systems where the cross-effects are more complex to understand). One limitation of this approach is that when strictly constraining the operation of hydropower, only coal[1] and diesel are left for the provision of flexibility, which could influence the total costs. In a larger system that would be equivalent to constraining all existing hydropower plants. However, in reality, not all hydropower plants are equivalently constrained, due to differences in licensing (i.e. some will need to meet stricter operational constraints than others). Therefore, our scenarios are valid for providing general guidelines in systems where flexibility is scarce. In systems with many flexible power plants (e.g. gas), the resulting energy price profiles might be less variable (Kern and Characklis, 2017). Our estimations may be less transferable to those situations.

Hydro-thermal power systems are strongly influenced by water availability. For example, a dry year usually translates to higher costs because the system becomes more reliant on fossil generation. Also, hydropower operations can depend on hydrologic conditions: for example, wet years are typically associated with larger, but more stable flows, in contrast with normal years where frequent peaking is observed as a consequence of having a great need to maximize the value of water (Kern and Characklis, 2017). This motivates us to explore three different hydrologic scenarios: dry, normal and wet years. From historical flow data (55 years) we used the k-means clustering method to divide the data into three groups, and then the years closest to their respective cluster centers were selected as representative. Fig. 3 shows the selected wet, normal, and dry year, which represent 15, 17, and 23 time series (of their corresponding cluster), respectively. All three hydrologic years are used to analyze the performance of each mitigation alternative. The combination of the three power systems and the three hydrologic years produces nine scenarios.

To get an idea about the variability of renewable resources and demand in these scenarios, see Fig. 4. Panel a), which shows the inputs for a whole year (green area corresponds to the combined wind and solar generation, and the blue area to the reservoir inflows, expressed in equivalent energy). For each time step, the gap between demand and variable renewable energy production (i.e. netload) must be covered by thermal generators or hydropower production (hydropeaking). Panel b) shows the resulting operation from the model for two selected weeks. Here, it becomes clear how variabilities in net load are matched with coal, diesel, and hydropower. The lower plot (b) shows how there can be spilled energy when hydropower ramps are constrained.

3.2. Mitigation alternatives: operational constraints, re-regulation reservoir, and battery energy storage systems

Here we will provide the details of the mitigation alternatives, starting with the MRR and MIF, followed by RRR and BESS.

In terms of operational constraints, we used a fixed value for MIF (5 m^3/s) and explored a wide range of MRR levels. However, for the sake of brevity, our discussion will focus on only two of them. The first MRR is very strict, allowing an hourly change in streamflow of only 10 m^3/s (equal to 3% of the installed capacity of the hydropower plant). This would correspond to a very stringent environmental regulation, which, as we will see, can restore the natural regime. The second one allows for hourly changes of 25 m^3/s. From a power system perspective, this is also strict (only 9% per hour). However, it allows going from 0 to 100% and back within a day, which from an ecological point of view is very unnatural (a natural

[1] It should be noted that the rate of change of power output in the coal operation is not constrained (it is not uncommon in certain places to use coal as a peaking technology) in the model. Given the similarity in operating costs per kWh for both coal and gas, we decided to omit gas technologies.

Table 1
Detail of power system scenarios.

Power plant type	Scenario 1 (20% RES)			Scenario 2 (30% RES)			Scenario 3 (50% RES)		
	Min power (MW)	Mean power (MW)	Max power (MW)	Min power (MW)	Mean power (MW)	Max power (MW)	Min power (MW)	Mean power (MW)	Max power (MW)
Hydropower reservoir	30	varies	300	30	varies	300	30	varies	300
Solar power plant	0	75	200	0	75	250	0	150	500
Wind power plant	0	75	210	0	75	265	0	150	530
Coal power plant	150	varies	300	150	varies	300	150	varies	300
Diesel Power Plant	0	varies	300	0	varies	300	0	varies	300
Demand	340	600	750	340	600	750	340	600	750

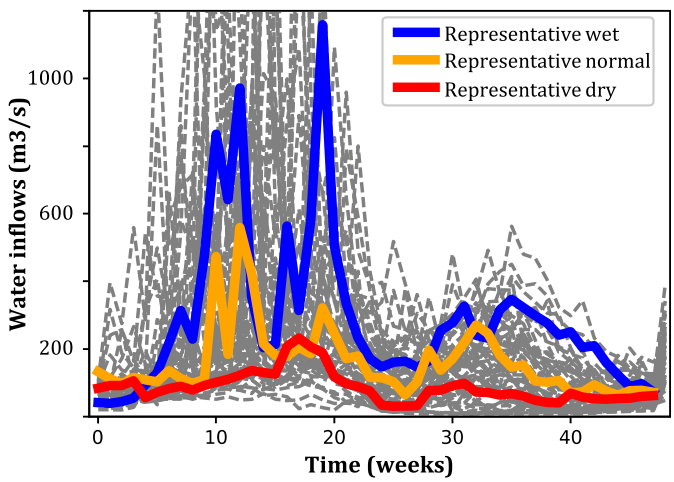

Fig. 3. Hydrologic years used in the case study.

flood, for example, takes several days).

Previous studies have shown that an effective size of the re-regulation reservoir (RRR) for hydropeaking mitigation (without considerations of costs) is somewhere below 4 h of storage capacity (Olivares, 2008). Larger sizes are better for reducing hydrologic alteration but are more costly. After trial and error, we defined a rather small size of 0.33 h of energy storage capacity (i.e. an energy storage capacity of 100 MWh for a hydropower plant of 300 MW). Apart from keeping costs low, another reason to choose the smallest RRR as possible (while still adhering to ramping constraints), is that larger RRR are inherently more challenging construction projects, given the potential for adversarial downstream water users and social opposition. The resulting dimension of our RRR is 0.36 Mm^3 -or a pool of, say, 200 m × 200 m and 9 m deep. We estimate the cost of building an RRR from a database of reservoirs used for flood protection (Keating et al., 2015), given the structural similarities involved. On that data, we applied a regression (Local Polynomial Regression). Fig. 5 shows the resulting cost distribution of RRR as a function of their volume. The cost-spread

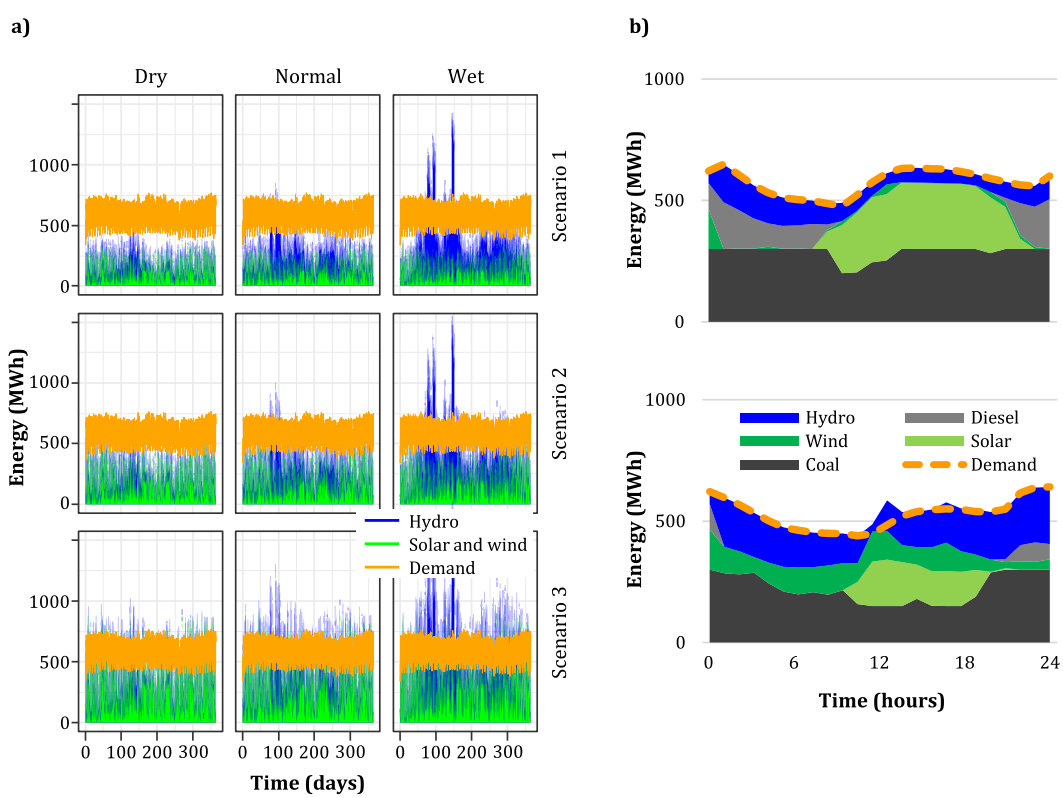

Fig. 4. Variability of energy profiles. a) Yearly energy inputs for the different scenarios (power systems and hydrologic years). b) Power system operation for selected weeks (output of the optimization).

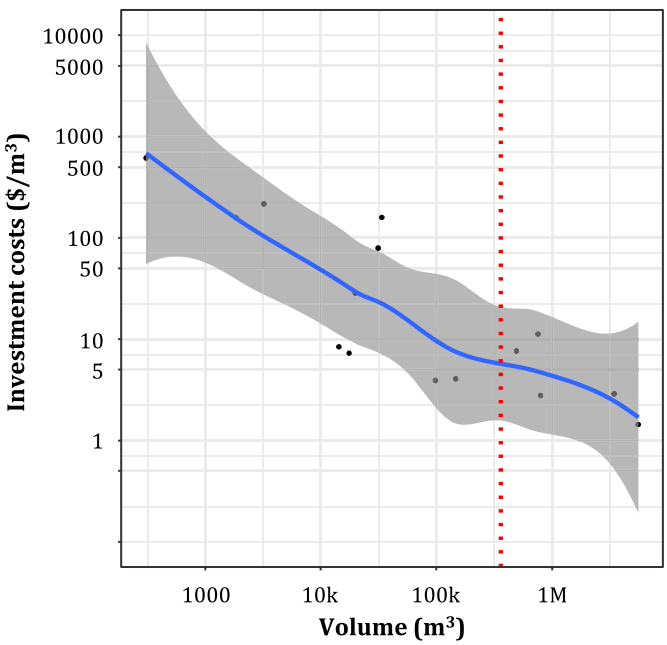

Fig. 5. Re-regulation reservoir cost prediction.

(gray band in Fig. 5) for one given volume reveals large differences between projects. This gray band englobes 95% of all costs, which implies that values above that band correspond to the 2.5% most expensive reservoirs costs (and the ones below the cheapest 2.5%). For our RRR size (0.36 Mm^3), indicated by the red line, we see that the expected, lowest 2.5%, and highest 2.5% costs are about 5, 2, and 25 $\$/m^3$. This cost range is fully explored in the discussion section.

The energy capacity of the battery is chosen to be equal to the RRR, i.e. 100 MWh (or 129 MWh if measured as the nominal storage capacity of the battery). BESS of this size can already be found in wholesale power systems today (U. S. Department of Energy, 2018). The power capacity is an additional design parameter and is determined using an expansion planning problem (external to our framework), attaining a value of 40 MW that makes economic sense for many of the scenarios considered in this study. This results in an energy-to-power ratio of 2.5 h, which is a very frequent value of current Li-ion installations (U. S. Department of Energy, 2018). Again, the rather small size of batteries (and RRR) responds to the stakeholder logic of finding the minimum investment able to comply with the environmental regulations. Larger sizes, of course, might be more effective but not as profitable as the ones considered here. Also for batteries, we performed a sensitivity to investment costs. Contrary to the RRR, Li-ion costs do not depend on location. Their cost rather depends on their worldwide deployment in the coming decades (i.e. experience curve of new technology). As there are many cost projections available, and we did not want to condition our results on only one particular study, we consequently explored the complete range of possible investments costs.

3.3. Cost-benefit analysis

The cost-benefit analysis relies on the calculation of discounted cash flows. A 40-year project horizon is considered for each alternative. For comparison, we use the Internal Rate of Return (IRR).[2] The higher this rate, the more attractive the investment is. A general rule is that the IRR should be at least above the discount rate of the company (which differs among each sector and company) in order to be considered a plausible investment. In the power sector, that rate is generally higher than 10%.

The "revenues" resulting from each mitigation alternative are calculated as the cost difference between a case in which the dam owner meets the MRR using operational constraints alone and case in which physical mitigation alternatives (RRR or BESS) are used. After finding the "revenues" associated with each mitigation alternative under each hydrologic condition (i.e. dry, normal, wet year), an annual expected value can be estimated by weighting each hydrologic year by its respective frequency in the historical record (see section 3.1). The expenses are the investment cost of each mitigation alternative. In the case of batteries, they additionally show replacement costs for the energy component to account for the gradual capacity fade and their final replacement every ten years.

4. Results and discussion

In this section, we will first introduce the operation of the mitigation alternatives, then we will compare their cost-effectiveness to finally discuss which alternative is more attractive. We wrap up the section with a discussion on uncertainties inherent to planning.

First, we will look at the operation of a sample week. Fig. 6 shows how the mitigation alternatives operate under the power system scenarios (columns) and hydrologic scenarios (rows). We can see how the business-as-usual discharges are the most

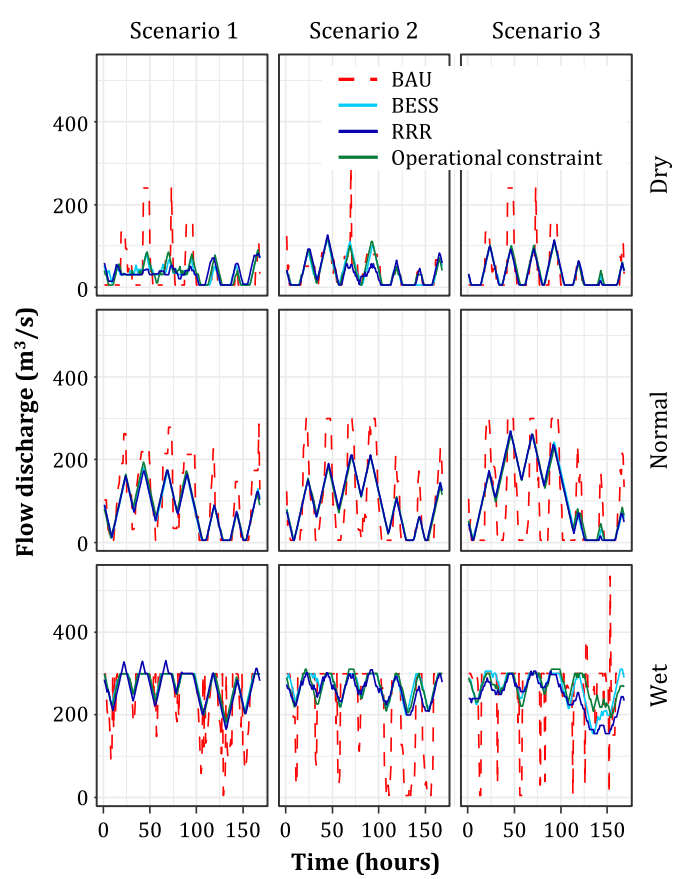

Fig. 6. Hydropower releases (of a sample week) of the different mitigation alternatives, for the different hydrologic and power system scenarios.

[2] Discount rate that makes the net present value equal to zero.

fluctuating for all scenarios. The release pattern gets smoothened by the enactment of the environmental constraints. The cases with an RRR or BESS are very similar in replicating this smoothened operation, as a direct result of obeying the (same) environmental constraints.

To draw a more generalized conclusion, we proceed to compute the subdaily streamflow fluctuations into one flashiness index, the R-B index (Baker et al., 2004). This index is large for highly pulsating flows and zero for constant releases. We calculate one R-B value for each run. That is, the 8760 hourly releases (associated with the optimal use of the hydroelectric dam within the larger context of the hydrothermal dispatch) are summarized into a single number. We repeated this for all power system scenarios, water type years, and MRR values ranging between 0 and 50 $m^3/s/h$.

Fig. 7 shows these resulting R-B indexes. From here, we see how the business as usual case (red-dashed lines) exhibits a large flashiness, which varies with the scenarios considered between 0.1 and 0.3. Wet years are characterized by a lower flashiness, whereas normal and dry years are more extreme. This is in-line with the literature (Olivares et al., 2015), although dry years can also show a more steady behavior if strong minimum flows are in place (Kern and Characklis, 2017). We also see from Fig. 6 that all mitigation alternatives perform similarly in making the flows smoother (again, as a direct response to the acting environmental constraints). We attribute the slight divergences (between a stricter MRR and the corresponding R-B index) to the fact that our tool only sees the MRR as a hard constraint and does not solve for the optimal R-B index (that relationship is not necessarily monotonic) and to convergence levels. However, in general terms, we can affirm that the more stringent the MRR, the lower the resulting flashiness index is. This is helpful for policy making, as an easy operational rule (MRR) effectively translates into improving an ecologically relevant (hydrological) index (R-B). The achieved R-B value depends on the hydrologic scenario, but the overall trend remains clear. In general terms, we see that constraining the releases with an MRR around 10–30 $m^3/s/h$ shows to achieve a flashiness around 0.05, for most scenarios. This is the *order of magnitude* of the natural flow's flashiness according to the literature (Zimmerman et al., 2010) (in our plot, the black dotted line shows a referential R-B index equal to 0.03), although the actual number depends on the river.

4.1. Cost-effectiveness of batteries and re-regulation reservoirs

Implementing MRR inherently makes hydropower less operationally flexible, leading to higher operational costs because the system now depends on more expensive thermal peaking technologies (e.g. diesel), which is shown in Fig. 8. We see how an MRR less stringent than 50 $m^3/s/h$ does not impact the system costs (lines are horizontal) for most scenarios. For MRR of around 20–30 $m^3/s/h$, the system begins to suffer from a more expensive operation, impacting the system by a couple of percents, which is consistent with previous studies (Haas et al., 2015). This is especially true for high renewable energy scenarios because they rely more strongly on operational flexibility. The operational costs increase most during dry years (the overall flexibility is scarcer). The opposite is true for wet years, with cost increases of about 10% or lower. The combination of dry years with highly renewable systems constitutes the most unfavorable situation in terms of cost increase under MRR.

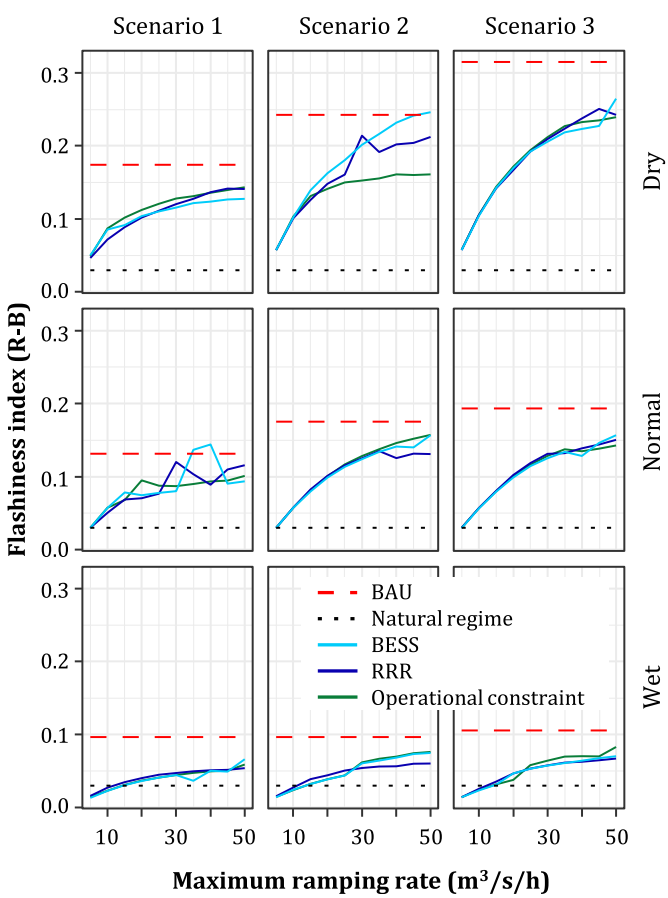

Fig. 7. Flashiness of releases of the different mitigation alternatives, for the different hydrologic and power system scenarios.

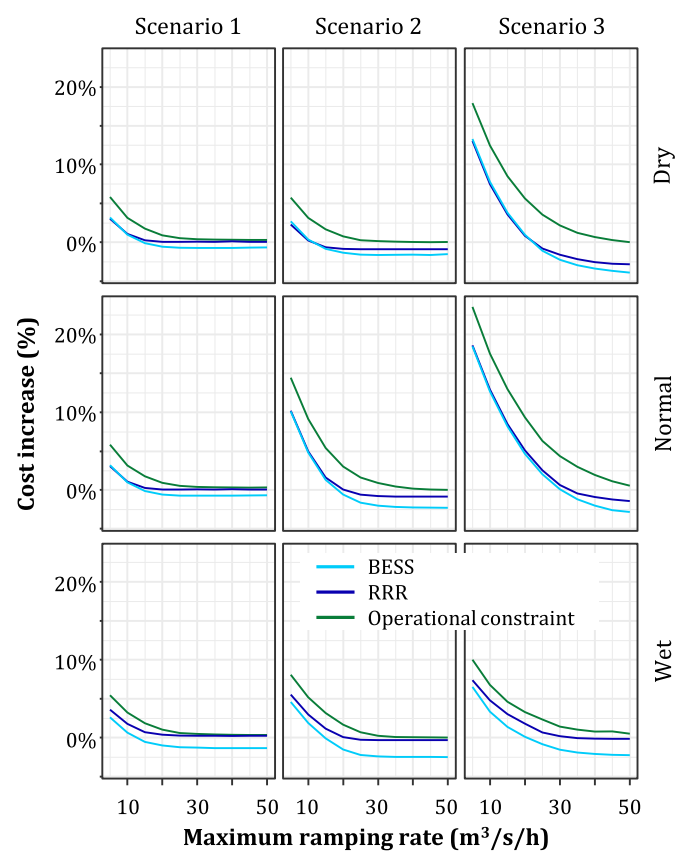

Fig. 8. Cost increase of the power system of the different mitigation alternatives, under the different hydrologic scenarios and power system configurations.

Fig. 8 also shows that the implementation of an RRR or BESS results in significant reduction in the system's operational costs for all scenarios. For looser MRR constraints, RRR performs slightly worse than BESS, in economic terms. This is because BESS can also provide other services (e.g. energy arbitrage). In very stringent MRR cases, both RRR and BESS converge to the same number. In these cases, BESS are mainly dedicated to meeting the MRR constraints.

Remember that the cost difference between the operational constraints (green line in Fig. 8) and a mitigation alternative in place (BESS and RRR, light and dark blue lines in Fig. 8) represent the "revenues" that are evaluated in the cost-benefit analysis (which is then weighted by the frequency of hydrologic year). In the next paragraphs, we will determine whether these "revenues" cover the capital cost of the mitigation alternatives. Given the sensitivity of our power system, which reacts for MRR equal to 30 m^3/s/h or stricter, we will focus our analysis on two particular cases: MRR = 10 and MRR = 25.

Although reservoirs are a mature technology, their investment costs vary broadly with location. To provide a more general recommendation, we explored a wide range of possible investment costs for RRR and calculated their profitability. This is shown in Fig. 9. The dotted color lines represent the IRR for the different hydrologic scenarios, and the thick black line the resulting weighted average. As a general observation, the profitability is positive (in most cases) and grows with lower investment costs. The dotted vertical line represents the "lower bound" for the RRR profitability (i.e. the 2.5% percentile of the most expensive RRR, see section 3.2). The intersection between this vertical and the expected IRR equals at least 25% for all scenarios (with the exception when MRR25 is applied to scenario 1). In other words, 97.5% of possible RRR costs could give us more than 25% expected IRR. Comparing scenarios 1 to 3, it becomes clear that the IRR increases as more renewable sources are introduced to the system. More stringent operational constraints, i.e. smaller MRR (moving from the right to left column in Fig. 9), translate into higher profitability in all power system scenarios.

For BESS, to capture the cost uncertainty inherent to new technologies, we also explored a wide range of investment costs. Note that BESS have two cost components, one for the energy capacity ($/kWh, related to the battery packs) (Curry, 2017) and one for the power capacity ($/kW, related to the inverter) (Child et al., 2017a). As a consequence, we decided to plot the results in the form of IRR-isoquants. In Fig. 10, the x-axis and the y-axis are inputs (investment costs for energy and power), and the straight black lines are our outputs (IRR). The colored points are cost-projections for the next years from recent studies (Child et al., 2017b). For example, the area below the black-dotted line corresponds to all the investment cost combinations that reach profitability above 40%. Using the cost projections, this would be reached in 2050 (for scenarios 2 with MRR10).

The least convenient case is the power system with lower shares of renewables (scenario 1 in Fig. 10). Here, BESS become profitable (IRR>10%) only in the long-term when stringent MRR are applied.

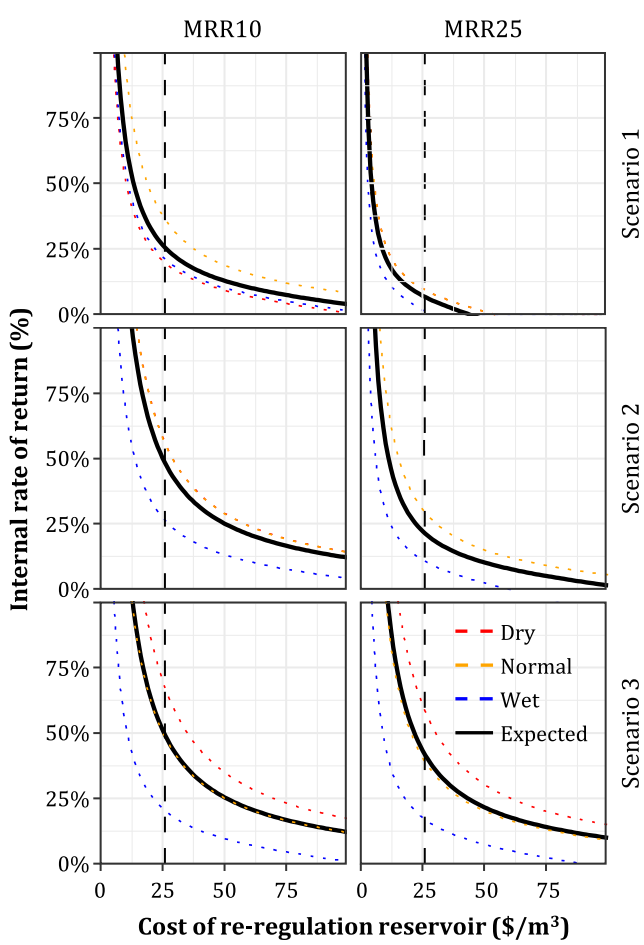

Fig. 9. Profitability of re-regulation reservoir under different reservoir costs assumptions, for the different hydrologic and power system scenarios.

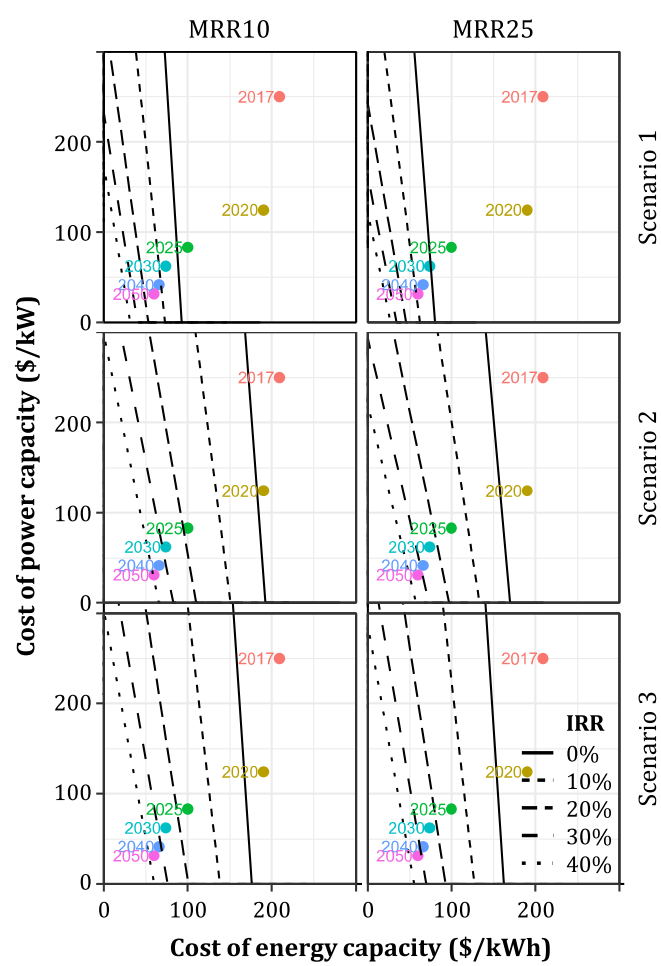

Fig. 10. Profitability of BESS under different cost assumptions, for the different hydrologic and power system scenarios.

For medium and high shares of renewables (scenarios 2 and 3), the profitability of BESS is below 10% before 2020, making it unattractive until that year. In 2025 a major jump happens: the IRR is above 15% for most cases, which is highly appealing. After that year the situation keeps on improving.

4.2. Batteries or re-regulation reservoirs for mitigation of hydropeaking?

The cost-benefit analysis shows that an RRR is cost-effective for a very broad range of possible project capital costs. A more stringent maximum ramping rate makes it even more attractive. This also holds for highly conservative cost assumptions for the RRR. However, the cost-benefit analysis does not take into account the time needed for constructing the RRR nor how the construction could potentially interfere with hydropower operation (i.e. lower head in downstream cascading plants or thermal power generation during the construction). Since construction cost and duration can vary greatly between sites, a more detailed RRR analysis is suggested for future work and for site-specific analysis.

For BESS, results suggest that they will be a cost-effective mechanism for allowing power systems to reclaim the value of peaking hydropower that may be lost to regulatory constraints in the near future. Current battery cost projections show them to be cost-effective (>10% expected IRR) from around 2025 onwards for systems with mid and high shares of renewables. The deployment of BESS in real power systems shows that they are already attractive in providing other services such as power reserves and energy arbitrage (Haas et al., 2018a), even in the absence of environmental constraints. This implies that the optimal size and operation of the BESS depends on different power system services in place (and their pricing scheme). Meeting operational constraints can be understood as an environmental service, which could become yet another stream of income of BESS.

BESS could be preferred if a re-regulation reservoir is not feasible, for example, due to land unavailability or social opposition. In the future, BESS could be the preferred alternative, especially with the increasing share of renewable energy in power grids. This is especially relevant for dams that need re-licensing. If the cost of building an RRR is high, the results show that a BESS can be a competitive alternative in the near future. BESS should begin to enter into discussions related to hydropeaking mitigation, especially given the typically long duration (e.g. 30 years) of operating license agreements at many dams.

For example, in the US, 10 GW of hydropower capacity is scheduled to go through the re-licensing process before 2025, and another 16 GW before 2030 (Federal Energy Regulatory Commission, 2018). During this process, the legally binding operational balance between dam operations and environmental impacts (including any potential restrictions on hydropower peaking) will be fixed for another period of 30 years. If power systems soon have a wider range of cost-effective options (i.e. BESS) for offsetting the economic penalties associated with ramping restrictions, this information could be directly useful in informing re-licensing discussions.

In summary, RRR are highly cost-effective, even using high-cost assumptions. In contrast, BESS can only be cost-effective starting from 2025. The cost-effectiveness of BESS can only match that of re-regulation reservoir if the cost of building an RRR is high, after 2030.

4.3. Limitations, uncertainties, and future work

There are several sources of uncertainties inherent to investment planning. To systematically assess the financial attractiveness of two alternatives for hydropeaking, we designed a wide range of scenarios. We explored a broad spectrum of investment cost parameters (for BESS and RRR), varying levels of constraints on hydropeaking, different power system configurations, and different water availability represented by hydrologic years; and attained in total about 5000 scenarios. Some sources of uncertainties that we did not consider are detailed below.

As expected, we detected that the profitability highly depends on the power system configuration, such that we recommend to run numbers specific to each case if the generation mix differs from ours, or if particular pricing mechanisms are in place. Particular attention should be directed to the available sources of flexibility (e.g. storage, peaking technologies, transmission). More flexible systems could delay the year in which BESS become viable, but it doesn't seem like something that would impact the relative performance of RRR vs. BESS.

For integrating renewable generation, both variability and uncertainty need to be addressed. In the present study, we tackled the variability by considering a full year with hourly resolution (and different weather years) but did not deal with the uncertainties as our optimization problems were deterministic. Accounting for forecast errors would likely increase the profitability of storage, because of their inherent ability to move energy through time. Our approach can be seen equivalent to operating the storage devices in the day-ahead market, without participating in the reserve markets.

Impact of climate change on hydrologic regimes is another point that worries energy planners. In general, the trend in Chile is a growing arid zone, with more intense flood events. From Fig. 9, we see that especially in dry years, the attractiveness of BESS/RRR is higher than in other years. In other words, in a system of more fluctuating energy production (including river runoffs), flexibility (BESS/RRR) becomes more valuable.

For future work, there is room for improvement in implementing time-varying operational constraints. For example, in many watersheds, the need for environmental flows change throughout the year (Arthington et al., 2006). This may change the performance of the mitigation alternatives across the different hydrologic years considered. Finally, in our case study, we considered the minimum sizes of RRR and BESS that are able to reproduce the natural flow regime; larger sizes would exhibit an even smoother flow, but in a direct trade-off with the profitability.

5. Conclusions and future work

In this study, we determine whether battery energy storage systems (BESS) are an efficient mechanism to reduce the impacts of hydropeaking. We compare their techno-economic performance in reducing the impact of subdaily hydropeaking with a re-regulation reservoir (RRR).

For the comparison, we used a hydrothermal dispatch model applied to a hypothetical test system under different levels of renewable energy penetration. In all scenarios, the business-as-usual case (without any limits on downstream variations in flow) is compared to cases where environmental constraints (in the form of maximum ramping rates and minimum instream flows) are imposed on the hydropower plant. The enactment of environmental constraints leads to additional system-wide operational costs, due to increased reliance on more expensive fossil-fuel resources for peaking. We study how an RRR and a BESS can reduce that additional cost.

The considered scenarios of environmental constraints result in flashiness indexes close to the natural regime. Both RRR and BESS can help to restore the natural regime at lower costs than using environmental flows alone.

The techno-economic analysis shows that an RRR is extremely cost-effective for a very broad range of possible investment costs. However, we did not consider uncertainties arising from potential social opposition and interference with downstream hydropower operations (i.e. lower head). Current battery cost projections show them to be cost-effective for hydropeaking mitigation (internal rate of return >10%) from around 2025 onwards for power systems with medium and high shares of renewables. More stringent environmental constraints make both solutions significantly more attractive. After 2030, BESS can match the cost-efficiency of RRR, but only if the construction costs of the latter are high. We delivered the resulting profitability of BESS and RRR in curves, such that they can be applied elsewhere for any arbitrary cost projection.

As future work, we recommend focussing on dynamic (variable over the year) environmental constraints. Yet another direction is understanding how the profitability of BESS and RRR evolve in more complex systems, as many hydropower dams going through relicensing that gradually need to meet more demanding environmental constraints. In the end, both BESS and RRR are a viable option for making hydropower reservoirs more ecologically sound.

Overall, understanding how hydropower can deliver operational flexibility to support highly renewable systems, without deteriorating riverine ecosystems is a key challenge for cleaner power production. Our findings offer new insights for decision-makers in the areas of combined energy system, and watershed and ecosystem management.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jclepro.2018.11.040.

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