Medium-term scheduling of a hydropower plant participating as a price-maker in the automatic frequency restoration reserve market

Juan I. Pérez-Díaz[1], Ignacio Guisández[1], Manuel Chazarra[1], Arild Helseth[2]
[1] Universidad Politécnica de Madrid. Department of Hydraulic, Energy and Environmental Engineering. c/ Profesor Aranguren 3, 28040 Madrid, Spain
[2] SINTEF Energy Research, Sem Saelands vei 11, 7465 Trondheim, Norway
Corresponding author e-mail: ji.perez@upm.es

Abstract

This paper presents a novel optimization model for the calculation of the water value of a hydropower plant. The model has a time horizon of 1 year with 1-day decision stages, considers sales of both energy and frequency restoration reserves (FRR) and is solved by stochastic dynamic programming. The novelty of the model is that it considers the producer's price-making ability in the FRR market. The proposed model is used to obtain the water values of an existing hydropower plant. The water values are then used to simulate the day-ahead scheduling of the hydropower plant in a 100-year scenario. The results are compared to those obtained without considering the producer's price-making ability in the FRR market. The profit increase is modest compared to the uncertainty existing in the day-ahead scheduling in all analysed cases. However, the water spillage is significantly lower if the producer's price-making ability in the FRR market is considered when computing the water value. This last result may have important implications for the plant's operation, especially when the reservoir is also used for the purpose of flood control, as the one used as case study in the paper, and many others all over the world.

Keywords: Hydroelectric power generation; Water value; Frequency restoration reserve market; Price-maker producer; Mixed integer quadratic programming; Stochastic dynamic programming.

Nomenclature

Abbreviations

EM day-ahead electricity market.
RM day-ahead automatic frequency restoration reserve market.
LP linear programming.
MILP mixed integer linear programming.
MIQP mixed-integer quadratic programming.
RDC residual demand curve.
SDP stochastic dynamic programming.
SDDP stochastic dual dynamic programming.
TSO Transmission System Operator.

Indexes/Sets

$d \in D$ Daily decision stage (1,…,d^{max}).
$e \in E$ Intervals of the plant aggregate power-discharge curve (1,…,e^{max}).
$e \in E_u$ Intervals of the plant aggregate power-discharge curve in which units 1,2,...,u are on.
$t \in T$ Hour within the day (1,…,24).
$u \in U$ Hydro unit of the plant (1,…,u^{max}).

Constants/Parameters

CF Conversion factor from m^3/s to Mm^3/h [0.0036 $(Mm^3/h)/(m^3/s)$].

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EV Rate of hourly evaporated water volume per flooded area [Mm^3/km^2].
G^{max} Maximum plant power generation [MW].
G^{min} Minimum plant power generation [MW].
I_t Intercept of the linear approximation of the residual demand curve in the day-ahead automatic frequency restoration reserve market in hour *t* [€/MW]
$K1^{bo}$ Coefficient of the linear approximation of the storage-maximum bottom outlet flow curve [$(m^3/s)/Mm^3$].
$K2^{bo}$ Coefficient of the linear approximation of the storage-maximum bottom outlet flow curve [m^3/s].
$K1^{ev}$ Coefficient of the linear approximation of the storage-flooded area curve [km^2/Mm^3].
$K2^{ev}$ Coefficient of the linear approximation of the storage-flooded area curve [km^2].
K^{sp} Conversion factor between the volume of water stored above the spillway level and the maximum flow through the spillway [$(m^3/s)/Mm^3$].
PER_t^{dw} Fraction of the committed downward reserve used in real-time [p.u.].
PER_t^{up} Fraction of the committed upward reserve used in real-time [p.u.].
Q^{min} Minimum flow that can be released through the hydro units [m^3/s].
Q^{max} Maximum flow that can be released through the hydro units [m^3/s].
Q_t^{wi} Water inflow to the reservoir in hour *t* [m^3/s].
QI^e Length of the *e*-th interval of the plant aggregate power-discharge curve [m^3/s].
QON^u Plant flow above which the *u*-th unit is started-up [m^3/s].
R_t Ratio between the upward and total reserve that the reserve offers must fulfil in hour *t*.
S_t Slope of the linear approximation of the residual demand curve in the day-ahead automatic frequency restoration reserve market in hour *t* [€/MW/MW].
V^{max} Maximum water storage [Mm^3].
V^{min} Minimum water storage [Mm^3].
V^{min} Minimum water storage [Mm^3].
V^{sp} Volume of water stored in the reservoir when it is full up to the spillway level [Mm^3].
Y^e Slope of the *e*-th interval of the plant aggregate power-discharge curve [$MW/(m^3/s)$].
α Wear-and-tear cost of the hydro units due to interhourly variations in the generated power [€/MW].
β Shut-down and start-up cost of the hydro units [€].
π_t^{em} EM price in hour *t* [€/MWh].
$\pi_t^{rtr,dw}$ Price in hour *t* of the net reserve used in real-time when it is downward [€/MWh].
$\pi_t^{rtr,up}$ Price in hour *t* of the net reserve used in real-time when it is upward [€/MWh].

Binary variables
asp_t = 1 if the stored volume at the end of hour *t* is above V^{sp}.
bfu_t = 1 if there is more upward reserve used in real-time than downward one in hour *t*.
off_t^u = 1 if the *u*-th hydro unit is shut-down at the beginning of hour *t*.
ol_t^u = 1 if the *u*-th hydro unit is on-line in hour *t*.
on_t^u = 1 if the *u*-th hydro unit is started-up at the beginning of hour *t*.
Non-negative variables
efp expected future profit [€].
r_t^{up} Upward reserve in hour *t* [MW].
r_t^{dw} Downward reserve in hour *t* [MW].
g_t Power generated in hour *t* [MWh].
g_t^{dec} Decrease in the generated power between hour *t*-1 and *t* [MW].

g_t^{inc} Increase in the generated power between hour t-1 and t [MW].
p_d Profit in the d-th decision stage [€].
q_t^{bo} Flow released through the bottom outlets in hour t [m^3/s].
q_t^{hp} Flow released through the hydro units in hour t [m^3/s].
q_t^{sp} Flow released through the spillway in hour t [m^3/s].
qi_t^e Flow released through the hydro units in hour t in the e-th interval of the plant aggregate power-discharge curve [m^3/s].
sv_d^{en} Endogenous state variables at the beginning of the d-th decision stage.
sv_d^{ex} Exogenous state variables at the beginning of the d-th decision stage.
ur_t^{dw} Net reserve used in real-time when it is downward [MWh].
ur_t^{up} Net reserve used in real-time when it is upward [MWh].
v_t Volume of water stored in the reservoir at the end of hour t [Mm^3].
v_t^{asp} Volume of water stored above the spillway level at the end of hour t [Mm^3].
v_t^{bsp} Volume of water stored below the spillway level at the end of hour t [Mm^3].
v_t^{ev} Volume of water evaporated in hour t [Mm^3].
$\bar{v}_T, \underline{v}_T$ Discrete values of the initial storage closest to v_T from above and below, respectively.
$\tilde{z}_d$ Optimal cumulative expected profit from the beginning of the d-th decision stage to the end of the planning period [€].

I. Introduction

Traditionally, operational decisions of hydropower plants were made by a centralized operator who sought to minimize the power system operation cost while meeting the electricity demand [1]. The process by which such centralized operator made operational decisions of both hydro and thermal power plants is a multistage decision process [2] which has often been decomposed into several decision processes, each with a different planning horizon (short-, medium- and long-term), degree of detail and treatment of uncertainty to make it numerically tractable [3]. The coordination between the medium- and short-term generation scheduling in centralized electricity markets has usually been realised by means of future cost functions that express the expected power supply cost as a function of the system's state at the end of the short-term scheduling horizon. The first derivative of the future cost function with respect to the volume of water stored in the system gives information about the opportunity cost of water, also known as the *water value* [4]. The water value represents the tradeoff between the immediate cost savings due to the immediate use of the available water and the expectation of the future cost savings due to the storage and later use of the water [5].

Since the beginning of the nineties, electricity markets all over the world have gradually experienced a continuous process of deregulation [6], [7]. As a consequence of the deregulation, the operational decisions of power plants are no longer made by a centralized operator but by generation companies. The goal of generation companies is not anymore meeting the electricity demand at minimum cost but to maximize their profit. In deregulated electricity markets the water value represents the tradeoff between the immediate gain due to the immediate use of the available water and the expectation of the future gain due to the storage and later use of the water [8].

Even though the structure of the existing deregulated electricity markets is country-specific, most of them are organised around a day-ahead wholesale electricity market (EM), where

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generation companies submit bids for selling energy in the following day [9]. Generation companies can correct forecast errors or unforeseen events close to real-time in the so-called intraday electricity markets [10], and can help the Transmission System Operator (TSO) ensure the power system reliability by providing the so-called ancillary services [11].

The first attempts to compute the water value in a deregulated electricity market considered only the sales of electricity in the EM were [12] and [13]. To the best of our knowledge, the work presented in [14] was the first one considering other markets different from the day-ahead electricity market in the medium-term generation scheduling of a hydropower plant. The authors of [14] considered the secondary load-frequency control (or automatic frequency restoration reserve) market operated by the Swiss TSO Swissgrid in the medium-term generation scheduling of a large open-loop pumped-storage power plant. According to the results obtained in [14], considering the secondary load-frequency control market operated by Swissgrid for the computation of the water value would have a minor impact on the power plant profit. The secondary load-frequency market of Swissgrid was later considered in [15] and [16] to compute the water value of a small hydropower system with pumping capacity.

The spinning reserve markets operated by the Norwegian TSO Statnett were considered when computing the water value in [17] and [18]. The medium-term generation scheduling models used in [17] and [18] are both based on stochastic dynamic programming (SDP) and stochastic dual dynamic programming (SDDP), as proposed in [13]. A scheduling horizon of 1 and 2 years was used in [17] and [18], respectively, with weekly decision stages in both cases. The decomposed weekly decision problem is formulated as a linear programming (LP) problem in both [17] and [18] and do not therefore consider binary decisions regarding the start-up or shut-down of the hydro units. As discussed in [17], this might lead to overestimate the ability of the hydropower system to sell spinning reserves. A set of linear constraints was added in [19] to the decomposed weekly decision problem in order to cope with the above-mentioned issue. The added constraints had previously been used to model the start-up costs of generating units and pumps in the medium-term generation scheduling of the Icelandic power system in [20], and were first proposed in [21]. The authors of [19] found that in periods with low energy prices and high reserve prices the SDP/SDDP model tended to operate the power station below the minimum output. A detailed short-term generation scheduling model based on mixed integer linear programming (MILP) is used in [19] to quantify the approximation errors of the SDP/SDDP model used to compute the water value. The water value obtained by the SDP/SDDP model (represented by cuts) were used in the short-term scheduling model to calculate the profit of the hydropower system under study in all the scenarios sampled in the last forward pass of the SDP/SDDP model. The average profit obtained with the MILP model turned out to be around 1 % lower than the one obtained by the SDP/SDDP model.

Similar constraints were added in [18] to discourage the model from operating below the station's minimum output. The results obtained in [18] are quantitatively similar to those presented in [14]: the consideration of the spinning reserve sales in the medium-term generation scheduling has a minor impact (~1 %) on the hydropower system's profit.

A simplified version of the decomposed weekly problem formulated in [18] was used in [22], without the above-mentioned discouraging linear constraints, to derive an analytical expression for the water value of a single hydropower reservoir in the same market context as in [18]. A

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few interesting conclusions about the influence of the spinning reserve capacity sales on the water value were drawn from the analytical expression and verified in a case study.

The consideration of start-up or shut-down decisions in [17], [18] and [22] would make the expected future revenue function (also referred to as profit-to-go [14] or cost-to-go function in centralized market contexts [23]) non-concave, and would therefore be necessary to “concavisate” it [24]. Instead, the authors of [25] chose to use an SDP-based medium-term generation scheduling model to compute the water value of a single hydropower reservoir, in the same market context as in [18], and to formulate the decomposed weekly decision problem as a mixed integer linear programming (MILP) problem, considering the status (on/off) of the hydro generators as binary decisions. The results obtained in [25] are quantitatively similar to those obtained in [14] and [18].

All the above-mentioned articles where the water value is computed in a multi-market context assume that the hydropower producer acts as a price-taker in both the energy and reserve markets. Some articles have dealt with the medium-term generation scheduling of hydropower producers whose bids may alter the clearing price of the day-ahead [24], [26] and intraday electricity markets [27]. However, as far as we know, there are no papers considering the ability of the hydropower producer to alter the clearing prices of the reserve market in medium-term hydropower scheduling. This research gap is the main motivation of this paper.

The influence of a power producer on the clearing prices in different markets depends on the producer’s size relative to each market's demand [28]. Taking as a reference the criterion used in [29], the assumption that the reserve bids of a hydropower producer do not alter the clearing price of the reserve market is not very realistic. Just as an example, on 17 April/18 July 2018 43/40 electricity producers submitted reserve bids to the day-ahead automatic frequency restoration reserve market (hereinafter referred to as RM) operated by the Spanish TSO (REE), respectively, and only 4/10 of them would be considered as price-taker according to the criterion used in [29]. The gate closure time of the RM is 4 pm. The hourly marginal prices and reserves allocated to each participant are known by 4:30 pm. The allocated reserves are all paid at the market’s marginal price. The allocated reserves can be no, partly or wholly used in real-time. The real-time use of the reserves is paid at the marginal price of the manual frequency restoration reserves (known as tertiary regulation reserves in the Spanish power system).

The objective and contribution of this paper is twofold: a) to present a novel medium-term generation scheduling model for the computation of the water value of a hydropower plant participating as a price-taker in the EM operated by OMIE and as a price-maker in the RM; b) to assess how the producer’s price-making ability in the RM impacts it's expected profit.

The proposed medium-term scheduling model has been used to obtain the water values (policy) of a hydropower plant in an offline optimization process solved by SDP. Subsequently, the water values were used to simulate the day-ahead scheduling of the plant in a 100-year synthetic scenario. The simulation is performed by running a day-ahead scheduling model on a rolling horizon basis. The water values obtained by the medium-term scheduling model are used as input to the day-ahead scheduling model, and are not updated during the simulations. Simulations were also performed using water values obtained from two other medium-term scheduling models: one assuming participation only in the EM as a price-taker, and the other assuming participation as a price-taker in both markets. The results of the simulations have been duly compared to each other in terms of the plant's profit and water spillage. The scheduling model is formulated in the context of the Spanish electricity market but can be easily adapted to be used in other electricity markets where both energy and reserves are allocated in day-ahead auctions. In order to make the second contribution of the paper applicable to other reserve markets, we have performed the above-mentioned comparison in some additional cases.

The rest of the paper is organized as follows. Section II describes the proposed medium-term generation scheduling model. Section III presents the main data of the case study. The results of the paper are discussed in section IV and the conclusions are duly drawn in section V.

II. Medium-term scheduling model

The model has a scheduling horizon of 1 year with 1-day decision stages *d*. The objective of the model is to maximise the expected profit of the hydropower plant for the entire scheduling horizon. The hydropower producer is assumed to be risk-neutral and to participate as a price-taker in the EM and as a price-maker in the RM. The EM and the RM are assumed to be simultaneously cleared. The daily decision stages *d* are divided into hourly periods t, consistently with the programming periods of the EM and RM. Information about the EM and RM can be found in the websites of the OMIE and REE.

In Spain there are 1,228 hydropower units distributed in a few hundred reservoirs with a storage capacity ranging from .25 to almost 3,000 Mm^3. 51 companies submit selling bids in the EM on behalf of their own or others' hydropower plants. Each company has its own planning/decision models and these are confidential. Around 50 % of the Spanish hydropower reservoirs are classified by the system's TSO as "annual regime reservoirs". These reservoirs have a seasonal storage capacity, i.e. they're able to store the natural water inflows for a period of several months. The use of a scheduling horizon of one year is suitable for these reservoirs.

The model is solved by means of an SDP approach similar to the one used in [25]. This allows straightforward consideration of non-convexities, such as generator start-stop decisions. Moreover, the results obtained with the proposed model can help evaluate the importance of price-maker effects in the medium-term scheduling.

Three exogenous stochastic state variables sv_d^{ex} are considered in the model: the daily water inflow volume, the daily average EM price and the daily average residual demand curve (RDC) of the RM. The hydro storage volume is a state variable endogenous to the optimisation problem. The daily water inflow volume has been modelled as a discrete Markov chain, whereas the other exogenous stochastic state variables have been modelled in two different ways. The rationale for this is explained in section III.2. The average RDCs have been modelled as linear monotonic decreasing functions defined each by an intercept and a slope, as in [30]. According to [31], the RDCs of the RM can be linearly approximated with an acceptable approximation error. There exist other approaches which might be useful to consider the competition between producers in the RM, such as agent-based modelling or game theory techniques. However, these approaches are out of the scope of the paper.

The future expected profit at the beginning of decision stage *d* for a certain system state $\{sv_d^{en}, sv_d^{ex}\}$ is given by the well-known Bellman equation (1), where x_d represent the set of

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decision variables in decision stage d, and can be recursively calculated by decomposing the problem into daily subproblems.

$$\tilde{z}_d(sv_d^{en}, sv_d^{ex}) = max\{p_d(x_d, sv_d^{en}, sv_d^{ex}) + \mathbb{E}[\tilde{z}_{d+1}(sv_{d+1}^{en}, sv_{d+1}^{ex})|sv_d^{ex}]\} \quad (1)$$

The decomposed daily decision problem has been formulated as a mixed-integer quadratic programming (MIQP) problem described by (2)-(23). For this problem, the realisation of the exogenous stochastic state variables is assumed to be known for the first stage d. This is one of the two reasons why we have chosen to use daily decision stages instead of weekly ones (see the second reason in section III.1). Assuming a perfect foresight of the RM prices 1-week ahead is too optimistic. The initial state is defined by the initial storage v_0 (which is the only endogenous state variable sv_d^{en}) and the above-mentioned exogenous stochastic state variables sv_d^{ex}. The initial storage is discretised in N_{en} values. The exogenous stochastic state variables are discretised in N_{ex} nodes, each containing information of the three variables. Note that the day index has been omitted in the formulation, except to indicate change of day in a few equations. The decision variables (unknowns) x_d of the decomposed daily decision problem are: the power generated, upward and downward reserve, hydro units' status (on/off), start-ups and shut-downs, flow released through the hydro units, the spillway and the bottom outlets, the volume of water evaporated in hour t, the volume of water stored in the reservoir, above and below the spillway level at the end of hour t, and the increase/decrease in the generated power between hour t-1 and hour t.

$$\tilde{z}_d(v_0, sv_d^{ex}) = max\left\{\sum_{t\in T}\left[\pi_t^{em} \cdot g_t + \left(I_t + S_t \cdot r_t^{up}\right) \cdot \frac{r_t^{up}}{R_t} - \alpha \cdot \left(g_t^{dec} + g_t^{inc}\right)\right.\right.$$
$$\left.\left. - \beta \cdot \sum_{u\in U}(off_t^u + on_t^u)\right] + \sum_{sv_{d+1}^{ex}\in N_{ex}}[\mathbb{P}(sv_{d+1}^{ex}|sv_d^{ex}) \cdot \tilde{z}_{d+1}(v_T, sv_{d+1}^{ex})]\right\} \quad (2)$$

$$v_t = v_{t-1} - v_t^{ev} + CF \cdot \left(Q_t^{wi} - q_t^{hp} - q_t^{bo} - q_t^{sp}\right);\ \forall\, t \in T \quad (3)$$

$$V^{min} \le v_t \le V^{max};\ \forall\, t \in T \quad (4)$$

$$v_t^{ev} = EV \cdot (K1^{ev} \cdot v_t + K2^{ev});\ \forall\, t \in T \quad (5)$$

$$q_t^{bo} \le K1^{bo} \cdot v_t + K2^{bo};\ \forall\, t \in T \quad (6)$$

$$q_t^{sp} \le K^{sp} \cdot v_t^{asp};\ \forall\, t \in T \quad (7)$$

$$v_t = v_t^{asp} + v_t^{bsp};\ \forall\, t \in T \quad (8)$$

$$v_t^{asp} \le (V^{max} - V^{sp}) \cdot asp_t;\ \forall\, t \in T \quad (9)$$

$$V^{sp} \cdot asp_t \le v_t^{bsp} \le V^{sp};\ \forall\, t \in T \quad (10)$$

$$q_t^{hp} \ge QON^1 \cdot ol_t^1 + \textstyle\sum_{u=2}^{u^{max}}[(QON^u - QON^{u-1}) \cdot ol_t^u];\ \forall\, t \in T \quad (11)$$

$q_t^{hp} \leq QON^2 \cdot ol_t^1 + \sum_{u=2}^{u^{max}-1}[(QON^{u+1} - QON^u) \cdot ol_t^u] + (Q^{max} - QON^{u^{max}}) \cdot ol_t^{u^{max}}; \ \forall\, t \in T$ (12)

$ol_t^u \geq ol_t^{u+1}; \ \forall\, u \in U \ \mid u < u^{max} \wedge \forall\, t \in T$ (13)

$on_t^u - off_t^u = ol_t^u - ol_{t-1}^u; \ \forall\, u \in U \wedge \forall\, t \in T$ (14)

$on_t^u + off_t^u \leq 1; \ \forall\, u \in U \wedge \forall\, t \in T$ (15)

$q_t^{hp} = QON^1 \cdot ol_t^1 + \sum_{e \in E} qi_t^e \,; \ \forall\, t \in T$ (16)

$qi_t^e \geq QI^e \cdot ol_t^{u+1}; \ \forall\, e \in E^u \wedge \ \forall\, u < u^{max} \wedge \forall\, t \in T$ (17)

$qi_t^e \leq QI^e \cdot ol_t^u; \ \forall\, e \in E^u \wedge \forall\, u \in U \wedge \forall\, t \in T$ (18)

$g_t = G^{min} \cdot ol_t^1 + \sum_{e \in E}(Y^e \cdot qi_t^e)\,; \ \forall\, t \in T$ (19)

$g_t^{inc} - g_t^{dec} = g_t - g_{t-1}; \ \forall\, t \in T$ (20)

$r_t^{up} \leq \frac{G^{max}}{u^{max}} \cdot \sum_{u \in U} ol_t^u - g_t; \ \forall\, t \in T$ (21)

$r_t^{dw} \leq g_t - G^{min} \cdot \sum_{u \in U} ol_t^u\,; \ \forall\, t \in T$ (22)

$r_t^{up} = R_t \cdot (r_t^{dw} + r_t^{up}); \ \forall\, t \in T$ (23)

The objective function (2) maximizes the income obtained from the energy and reserve sold in the EM and RM minus the start-up, shut-down and wear and tear cost of the hydro units, plus the future expected profit, which is given by the last summation term of (2). Traditional ramp up/down constraints and minimum up/down times are not considered in the paper. Instead, we consider in the objective function the wear and tear cost of interhourly power variations, as well the hydro units' start-up and shut-down costs. Parameters α and β were estimated from [32] and [33], respectively. $\tilde{z}_{d+1}$ is modelled by means of a piecewise linear function similar to the one used in [25] (equations (4)-(6) in that paper). This piecewise approximation is equivalent to a linear interpolation. It should be noted that v_T is a decision variable of the problem. In general, this variable does not take any of the N_{en} values into which the initial storage has been discretized. Thus, for a given v_T, $\tilde{z}_{d+1}(v_T, sv_{d+1}^{ex})$ is linearly interpolated from $\tilde{z}_{d+1}(\bar{v}_T, sv_{d+1}^{ex})$ and $\tilde{z}_{d+1}(\underline{v}_T, sv_{d+1}^{ex})$. Eq. (3) represents the water mass balance. The storage is limited by Eq. (4). The evaporation volume is estimated by Eq. (5) as a function of the flooded area. The maximum flow that can be released through the bottom outlets is limited by Eq. (6). The maximum flow that can be released through the spillway is limited by Eqs. (7)-(10). Eqs. (11)-(19) are used to model the plant's aggregate generation characteristic and to calculate the status of the hydro units. A piecewise linear power-discharge curve is used in each decomposed daily decision problem to model the plant aggregate generation characteristic. The curve is selected as a function of the initial storage v_0 and is therefore known a priori. The curve is defined from the following parameters: G^{min}, G^{max}, QI^e, Q^{max}, QON^u and Y^e. These parameters vary as a function of the initial storage. We have not explicitly included this dependence in the formulation for the sake of brevity. The variation in head between days is therefore considered through the proper

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selection of the piecewise linear power-discharge curve. Intraday head effects are neglected in the paper, accordingly to [34]. Eqs. (11) and (12) are used to calculate the maximum and minimum flow that can be released through the on-line hydro units. Eq. (13) guarantees that the hydro units are brought on-line in the proper order. Eq. (14) and (15) are used to calculate the number of start-up and shut-down manoeuvres of each unit. Eqs. (16)-(18) are used to calculate the flow released through the on-line hydro units. Eq. (19) is used to calculate the power generated by the on-line hydro units. The interhourly variation of power output is calculated in Eq. (20). Eqs. (21) and (22) are used to limit the reserve capacity, as a function of the on-line hydro units. Eq. (23) is used to meet the ratio between the upward and total reserves set by the TSO.

The SDP solution procedure is summarised in the following pseudocode, where the index *j* refers to the iteration step of the procedure.

$j \leftarrow 0;\ \tilde{z}_d^j(v_0, sv_d^{ex}) \leftarrow 0;\ \Delta \leftarrow \infty$
    while $\Delta > \varepsilon$ do
        $j \leftarrow j + 1$
        for $d = d^{max}, \ldots, 1$ do
            for $v_0 = v_0^1, v_0^2, \ldots, v_0^{N_{en}}$ do
                Select power-discharge curve
                $(QON^1, \ldots, QON^{u^{max}}; QI^1, \ldots, QI^{e^{max}}; Q^{max}; G^{max}; G^{min})$
                for $sv_d^{ex} \in N_{ex}\ (\pi_t^{em}, I_t, S_t, R_t)$ do
                    Solve (2)-(23)
                end for
            end for
        end for
        $\Delta \leftarrow max\{(\tilde{z}_d^j(v_0, sv_d^{ex}) - \tilde{z}_d^{j-1}(v_0, sv_d^{ex}))/\tilde{z}_d^{j-1}(v_0, sv_d^{ex})\}$
    end while
$\tilde{z}_d(v_0, sv_d^{ex}) \leftarrow \tilde{z}_d^j(v_0, sv_d^{ex})$

Once the SDP algorithm has converged, the water values of the hydropower plant are computed by a discrete differentiation of the last summation term of (2) with respect to sv_{d+1}^{en}. A similar pseudocode is used in [25]. The theoretical background on which this recursion solution procedure is based is explained in detail in [35].

III. Case study

III.1 Power plant data

The most important data of the hydropower plant used as case study are included in Table 1. The hydropower plant is located in the Northwest of Spain, sells energy in the EM, and is considering the possibility of selling reserves in the RM. As can be seen in Table 1, each of the three power plant's units has a spinning reserve capacity of 81.9 MW (104.2-22.3). The plant's spinning reserve capacity when the three units are running is equivalent to 27/35% of the maximum hourly requirement for upward/downward reserve (900/700 MW) in the RM. The second reason (the first reason is explained in section II) why we have chosen to use daily

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decision stages, instead of weekly ones, is the relatively short period necessary to empty the reservoir at maximum flow (approximately 3.5 weeks).

The historical series of daily water inflows were taken from the web page of the "Centro de Experimentación y Obras Públicas" (CEDEX) (http://ceh-flumen64.cedex.es) and correspond to the years 1963-2005. Lag-1 autocorrelation of the daily average water inflow is 0.80, which can be considered a notable autocorrelation, and for this reason, it was modelled as a lag-1 Markov chain with 5 discrete states, each representing a different "type" of daily average water inflow, namely: extraordinarily low, low, medium, high, extraordinarily high. The discrete values of the Markov chain have been obtained from the above-mentioned 43-year historical series. The lowest and highest historical values were used as the lowest and highest discrete states of the Markov chain and supposed to represent the lowest and highest 2-th percentiles of the historical series. The central part of the historical series was divided into three groups each with an equal frequency [36]. The mean values of the three groups were used as central discrete values of the Markov chain. The motivation to consider the highest and lowest 2-th percentiles of the historical series was to make the model as robust as possible [37]. The reservoir volume has been discretised into 9 equidistant values from previous experiences of the authors with this hydropower plant [34].

Table 1. Hydropower plant data.

Maximum reservoir water content (Mm^3)	644.6
Minimum reservoir water content (Mm^3)	71.0
Maximum water elevation (masl)	329.5
Minimum water elevation (masl)	270.0
Tailwater elevation (masl)	198.0
Number of hydro units	3
Type of hydro units	Francis
Number of penstocks	3
Maximum flow (m^3/s)	279 (3 x 93)
Minimum flow (m^3/s)	40
Maximum power (MW)	312.6 (3 x 104.2)
Minimum power (MW)	22.3

III.2 Energy and reserve markets data

The historical data of the EM and RM were taken from the website of OMIE (www.omie.es) and from the REE's information system (https://www.esios.ree.es/es), respectively. In the period 2010-2015, the lag-1 autocorrelation of the daily average energy and reserve prices were 0.77 and 0.66, respectively, whereas the cross-correlation between the two variables was -0.43. From these values, we chose to model the daily average energy price and the daily average RDC of the RM in two different ways, namely: each as an independent lag-1 Markov chain, and as a single lag-one joint Markov chain. The GARCH-ARIMAX and SARIMA models presented, respectively, in [30] and [38] have been used to generate a set of 200-year synthetic series of both the daily average EM price and the daily average RDC of the RM. The discrete states of the Markov chain of the daily average EM price were obtained from the above-mentioned synthetic series, by following an approach similar to the one used to build the Markov chain of the daily average water inflow. The discrete states of the Markov chain of the daily average RDC of the RM and the joint Markov chain of the daily average EM price and RDC of the RM have been obtained

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from the above-mentioned synthetic series, by applying the well-known *kmeans* clustering algorithm, in a similar way to [18]; both Markov chains have 3 discrete states. The above-mentioned SARIMA model has been used to generate a set of two-variable (intercept and slope of the daily average RDC of the RM) samples for each day of the scheduling horizon of the medium-term scheduling model (365 days). We have used the *kmeans* algorithm to determine 3 two-variable centroids (cluster centers), each representing approximately 1/3 of the samples, for each day of the scheduling horizon. Since the initialization of the *kmeans* algorithm in Matlab is by default random, we have run it a few hundred times and have selected the set of centroids representing quasi-equally distributed clusters that is provided by the *kmeans* algorithm more often. The discrete values of the Markov chain of the daily average RDC of the RM are the two-variable samples closest to the centroids of the set. This process has been performed every day in the scheduling horizon of the medium-term scheduling model (365 days). We have proceeded in a similar way to determine 3 three-variable (daily average EM price, intercept and slope of the daily average RDC of the RM) centroids for each day of the scheduling horizon and then select the discrete values of the joint Markov chain of the daily average EM price and RDC of the RM. In the period 2010-2015, the correlation between the daily average EM/RM prices and the daily average water inflow was -0.34/0.14, and has therefore been ignored in the paper.

In summary, a total number of 9 initial volumes x 5 water inflows x 3 pairs of EM price-RM RDC (9 initial volumes x 5 water inflows x 3 EM prices x 3 RM RDC) decomposed daily subproblems are solved at each daily decision stage *d* when the cross correlation between the daily average EM price and the daily average RDC of the RM is (is not) considered.

III.3 Simulations by short-term model

The day-ahead generation and reserve scheduling of the hydropower plant has been simulated in a 100-year synthetic scenario using the short-term MIQP model described by (3)-(27). The objective function of the model is given by Eq. (24). The model has a 24-h scheduling horizon and is aimed at maximizing the profit of the hydropower plant in the EM and RM, and from the real-time use of the reserves committed in the RM, assuming the hydropower plant participates as a price-taker in the EM and as a price-maker in the RM, and taking into account the start-up, shut-down and wear and tear cost of the hydro units, as well as the expected future profit, which is given by the last summation term of (24).

$$max\left\{\sum_{t\in T}\left(\pi_t^{em} g_t + \left(I_t + S_t r_t^{up}\right)\frac{r_t^{up}}{R_t} + \pi_t^{rtr,up} ur_t^{up} - \pi_t^{rtr,dw} ur_t^{dw} - \alpha\left(g_t^{dec} + g_t^{inc}\right) - \beta\sum_{u\in U}\left(off_t^u + on_t^u\right)\right) + \sum_{sv_{d+1}^{ex}\in N_{ex}}\left[\mathbb{P}\left(sv_{d+1}^{ex}|sv_d^{ex}\right)\cdot \tilde{z}_{d+1}\left(v_{24}, sv_{d+1}^{ex}\right)\right]\right\} \quad (24)$$

$$ur_t^{up} - ur_t^{dw} = PER_t^{up} r_t^{up} - PER_t^{dw} r_t^{dw} \quad \forall\, t\, \in T \ (25)$$

$$ur_t^{up} \le G^{max}\cdot bfu_t;\ \forall\, t \in T \quad (26)$$

$$ur_t^{dw} \le G^{max}\cdot (1 - bfu_t);\ \forall\, t \in T \quad (27)$$

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The simulations have been performed assuming a perfect forecast of the next day water inflow, and of all market random variables, namely: hourly prices of the EM (π_t^{em}), hourly RDCs of the RM (I_t, S_t), hourly prices of the reserve used in real-time ($\pi_t^{rtr,up}, \pi_t^{rtr,dw}$), and the percentage of the committed upward and downward reserve requested by REE in real-time (PER_t^{up}, PER_t^{dw}). The reserve committed in the RM can be no, fully or partially requested in real-time by the TSO, both upward and downward (25)-(27). The hydropower producer receives an additional income from the net reserve used in real-time when it is positive (upward) and has to pay for the net reserve used in real-time when it is negative (downward). The reserve used in real-time has an impact on the hourly flow released through the hydro units, and on the wear and tear cost of the hydro units. In order to consider such an impact $\left(ur_t^{up} - ur_t^{dw}\right)$ has been added to g_t in Eqs. (19) and (20). Note that the activation of reserves was not considered in the medium-term scheduling model presented in Section II. We chose to consider the real-time use of the committed reserve in the short-term scheduling in order to obtain a (to the possible extent) feasible operation schedule. Its consideration in the medium-term scheduling is a potential future line of research.

$\tilde{z}_{d+1}$ is used in the last summation term of (24) to compute the expected future profit as a function of the final storage volume. $\tilde{z}_{d+1}$ is the link between the medium- and short-term scheduling. It is obtained in the last iteration of the SDP solution procedure described in section II), and is modelled by means of a piecewise linear function similar to the one used in [25]. A piecewise linear approximation similar to the one used in [25] (equations (4)-(6) in that paper) is applied to the discrete values of $\tilde{z}_{d+1}$ and considered in the short-term MIQP model. Four different medium-term scheduling models have been used to compute $\tilde{z}_{d+1}$, namely:

- Model 1: considers that the hydropower plant participates only in the EM as a price-taker.
- Model 2: considers that the hydropower plant participates as a price-taker in both the EM and RM.
- Model 3: the one proposed in the paper without considering the cross-correlation between the daily average prices of the EM and the RDCs of the RM. It considers that the hydropower plant participates as a price-taker in the EM and as a price-maker in the RM.
- Model 4: the one proposed in the paper considering the cross-correlation between the daily average prices of the EM and the RDCs of the RM. It considers that the hydropower plant participates as a price-taker in the EM and as a price-maker in the RM.

The procedure to obtain $\tilde{z}_{d+1}$ is analogous across the four models. Of course, $\tilde{z}_{d+1}$ is weighted in (2) consistently with the transition probabilities of the Markov chains of the exogenous stochastic state variables considered by each model. The exogenous stochastic state variables of Model 1 are the daily water inflow volume and the daily average EM price. The exogenous state stochastic variables of Model 2 are the daily water inflow volume, the daily average EM price and the daily average RM price. The exogenous stochastic state variables of Model 3 and 4 are those described in section II. The objective function and constraints of Models 3 and 4 are identical (2)-(23). The objective function and constraints of Models 1 and 2 are not included in the paper for the sake of conciseness. Fig. 1 summarizes the procedure used to obtain the results presented in the next section of the paper.

The GARCH-ARIMAX and SARIMA models presented, respectively, in [30] and [38] have been used to generate the 100-year synthetic series of both the daily average EM price and the daily average RDC of the RM. The 100-year synthetic series of the daily average water inflow has been generated from the Markov chain used to model this variable for the computation of the plant's water value.

IV. Discussion of results

The formulation of the decomposed daily decision problems of Model 3 and Model 4 (2)-(23) is an MIQP formulation where the objective function is quadratic and all constraints are linear. The formulation of the decomposed daily decision problems of Model 1 and Model 2 is an MILP formulation. We have used CPLEX™ v12.2 to solve both MIQP and MILP problems. CPLEX™ uses a branch and cut algorithm to solve problems with integer variables and dual simplex to solve the LP/QP problems of the branch and cut tree of MILP/MIQP problems.

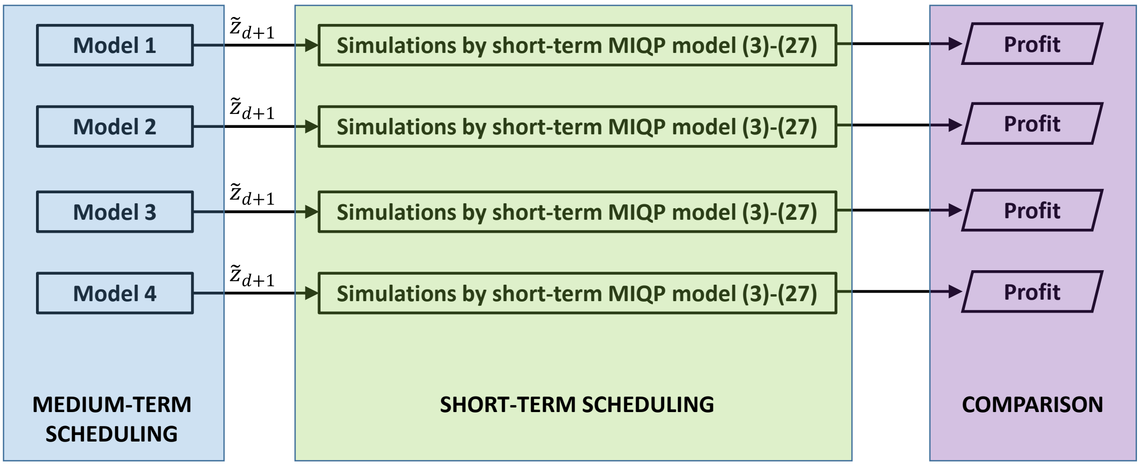

Fig. 1. Procedure followed to obtain the results.

Table 2 summarizes the CPU time and number of iterations necessary for Models 1-4 to converge, as well as the number of constraints, variables and integer variables of the decomposed daily decision problems of each Model.

Table 2. CPU time, iterations, equations and variables of Models 1-4.

	CPU time (s)	Number of iterations	Number of equations	Total number of variables	Number of integer variables
Model 1	52.047	3	1391	794	360
Model 2	240.768	3	1463	842	360
Model 3	391.975	4	1463	842	360
Model 4	56.649	3	1463	842	360

The profit obtained by the hydropower plant throughout the entire simulation period is shown in the last column [Profit (M€)] of Table 3. The water volume at the end of the simulation period when using the water value provided by Model 1/2/3/4 is 404.28/543.95/482.05/480.87 Mm^3. In order to make a fair profit comparison, we have calculated the future revenue the plant would get from the extra volume obtained with respect to the lowest volume (404.28) and have added this revenue to the profit obtained in the simulations when using the water value provided by Models 2-4. In order to calculate this extra revenue, it's necessary to attribute a monetary value to the extra volume with a unique criterion. We have used as valuation criterion the water value provided by Model 3 (i.e. the slopes of the profit-to-go-function). The profit shown in the last column of Table 3 includes this extra revenue. The results shown in Table 3 seem to indicate that considering the producer's price-making behaviour in the RM to compute the plant's water value brings a moderate additional profit of 0.09-0.12 % to the hydropower producer with respect to the case in which the water value is computed neglecting such an influence (Model 2).

Table 3. Results of the simulations.

Medium-term scheduling model	EM (M€)	RM (M€)	Operational cost (M€)	Profit (M€)
Model 1	4337.85	1361.20	-108.63	5590.42
Model 2	4482.26	1480.22	-122.00	5840.49
Model 3	4487.62	1478.71	-118.66	5847.68
Model 4	4482.33	1479.05	-119.06	5842.32

As can be seen in Fig. 2, the frequency curves of the reservoir volume corresponding to the cases where the water value was computed with Model 1, which may be considered as the standard approach followed nowadays by most hydropower producers, are by far the lowest ones. Each curve in Fig. 2 shows the percentage of hours (in per unit values) in the 100-year simulation period during which the reservoir volume given by the y-ordinate is exceeded. By contrast, those corresponding to the cases where the water value is computed with Model 2 are by far the highest. The "extreme" behaviour of both the models is due to the modelling inconsistencies existing between the short-term scheduling and the medium-term one, as discussed in [39] and [40]. Model 1/Model 2 tends to underestimate/overestimate the plant's water value [25], and for this reason, the short-term scheduling model tends to keep a lower/higher reservoir volume than in the cases where the water value was computed with Model 3 and Model 4, which are consistent with the power plant's operation strategy. The low reservoir volume obtained as a result of the short-term scheduling when using the water value provided by Model 1 has an impact on the available head and therefore limits power generation. This is the reason for the counterintuitive result that the revenue in the EM obtained when using the water value provide by Model 1 is lower than the one obtained with the water value provided by Model 2, even though Model 1 only considers sales of energy in the EM.

The only inconsistency between the short- and medium-term scheduling in the cases where the water value is computed with Model 3 and Model 4 is that the real-time use of the committed FRR has been only considered in the short-term scheduling. The reason for this is that the average hourly net energy (upward-downward) used in real-time for automatic frequency restoration purposes in the Spanish power system is usually a small fraction of the total committed reserve (e.g. in the first semester of 2017 it was 6.6 %).

Fig. 2 also shows the total volume of water spillage throughout the entire simulation. As can be seen in the Figure, even though the profit increase is moderate, the cases where the water value was computed with Model 3 and 4 have a total water spillage 29% lower than the case where the water value was computed with Model 2. The extra spillage obtained with the water values provided by Model 2 is 5.85e3 Mm^3 (compared to the one obtained with the water values provided by Model 3)[1]. Again, the reason for this extra spillage is that Model 2 overestimates of the plant's water value. The water value provided by Model 2 is higher than that provided by

[1] The average annual spilled volume is 58.5 Mm^3/year, which is approximately 2 % of the annual average water inflow (2876 Mm^3).

Models 3 or 4, because the former does not take into account the impact of the reserve offers on the RM prices. It should be noted that the total volume discharged through the turbines in the cases where the water value was computed with Model 2/Model 3 is 264708 Mm^3/270765 Mm^3 and that the average reservoir volume in these cases is 558/495 Mm^3. This difference in volume is equivalent to around 4 meters of gross head, and has an impact on the power production in terms of the MWh/Mm^3 rate of 9 MWh/Mm^3. These values explain why using the water value computed with Model 2 yields a profit close to the one obtained with the water values computed with Model 3 (see Table 3), with a higher water spillage and a lower volume of water discharged through the turbines.

This last result may have important implications for the hydropower plant's operation. This hydropower plant, as many others in Spain and other countries all over the world, is also used for flood control purposes. In these type of hydropower plants, flood control has usually a higher priority than other water usages, such as hydropower production, for obvious reasons. If we understand flood control as the set of control actions that are taken so as to avoid damages in the area downstream of the reservoir (river bed, river bank, floodplain), minimizing the amount of uncontrolled water spillage will always be beneficial. The extra spillage obtained in the case where the water value was computed neglecting the producer's price-making ability in the RM can be unacceptable from the point of view of the flood control.

Fig. 2 may make the reader think that participating in the RM will contribute to increase the water spillage. In order to be able to say so, it would be necessary to repeat the simulations using a short-term model consistent with Model 1, i.e. not considering the participation of the hydropower producer in the RM.

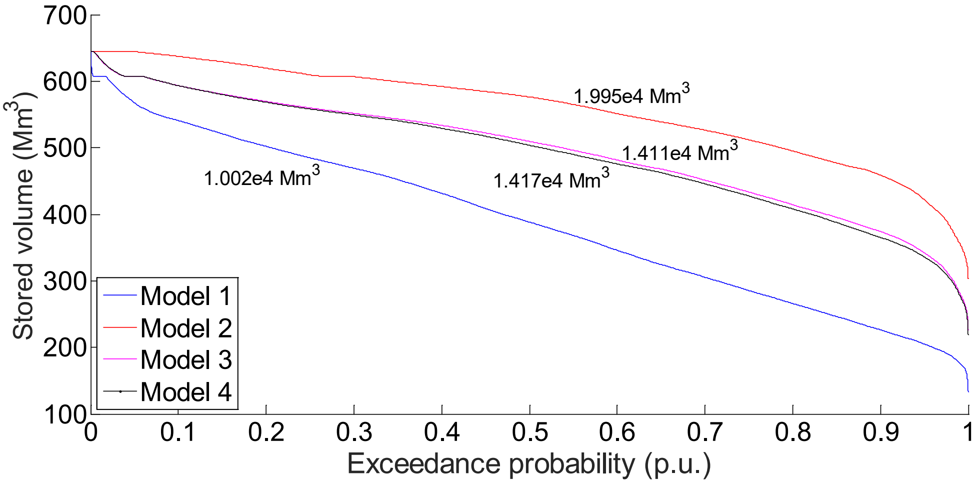

Fig. 2. Trajectories of the reservoir volume in the simulation period.

The following conclusions can be drawn from the results shown in Table 3 and Fig. 2: a) considering the participation of the hydropower plant in the RM when computing the plant's water values may contribute to increase the power plant's profit by 4.47-4.60 %, which is appreciably higher than the values reported for the reserve markets in Norway [18], [25] and Switzerland [14]; b) considering the influence of the hydropower producer on the clearing price of the RM when computing the plant's water value may contribute to further increase the power plant's profit by only 0.12 %, which can be considered modest compared to the uncertainty existing in the day-ahead scheduling, and to reduce the water spillage by 29 %; c) the cross-correlation between the hourly prices of the EM and RM is not significant enough to be

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considered when computing the plant's water values; d) if the producer does not consider him/herself a price-maker in the RM, his/her water values can be significantly overestimated. This does not have a large impact on the plants' profit, but for practical purposes it is not satisfactory to operate with wrong water values.

For the sake of completion, we want to note that the daily head variation obtained as a result of the simulations turned out to be lower than or equal to 2.24/1.38/1.69/1.71% of the plant's maximum gross head in 99 % of the days of the 100-year synthetic series. This supports our choice of not considering the intraday head variation in the plant's aggregate generation characteristic in the medium- or short-term scheduling models.

In order to test the sensitivity of the representation of the RM market on the results we have analysed 8 additional cases. We have created 4/4 synthetic series of the slope/intercept of the RM by multiplying the slope/intercept of the historical RDCs of the RM by a factor λ equal to 0.5, 0.75, 1.25 and 1.5. We have then proceeded as if these synthetic series corresponded to other reserve markets in which the impact of the plant's reserve offers has a different magnitude. The water value in these other reserve markets has been computed using only Model 2 and Model 3. Table 4 shows the results obtained in these additional cases (along with those corresponding to λ=1). As expected, the power plant's profit decreases as the slope of the RDCs becomes more pronounced (i.e. λ increases) and as the intercept of the RDCs decreases. The second/fourth last column of Table 4 shows the spillage/profit difference, expressed in percentage, when the water value is computed considering the influence of the hydropower producer on the clearing price of the RM. As can be seen in the Table, the profit increase is modest in all cases, even negative in some of them (from -0.27% to 0.32%), compared to the uncertainty existing in the day-ahead scheduling, whereas the spillage decrease is significant in all cases (from 19.63% to 35.54%). In the day-ahead generation scheduling of a hydropower plant that participates in the EM as price-taker and in the RM as price-maker, there are 3 main sources of uncertainty, namely: the water inflow to the reservoir, the EM price and the RDC of the RM. The uncertainty in the water inflow forecast is usually moderate, and given the size of the reservoir used in the case study, it is not expected to have an appreciable impact on the plant's generation schedule or revenue. According to [30], the uncertainty in the EM price forecast, measured as the mean absolute percentage forecast error, is between 15 % and 20 %. According to [38], the uncertainty in the RM RDC forecast, measured also as the mean absolute percentage forecast error, is between 20 % and 25 %.

The economic results are to some extent expected. High values of the RDC's slope imply a more pronounced decrease of the reserve price as a function of the producer's reserve offers, and therefore a lower profit in the RM, whereas higher values of the intercept imply a higher reserve price, and therefore a higher profit in the RM. This is clearly observed in the last column of the Table where the ratio between the profit obtained in the RM and the EM is shown.

Table 4. Results of the additional cases.

λ Intercept	λ Slope	Medium-term scheduling model	DM (M€)	RM (M€)	Operational cost (M€)	Profit (M€)	ΔProfit (%)	Spilled volume (Mm^3)	ΔSpilled volume (%)	RM/DM (%)
1	0.5	**Model 2**	4435.00	1735.62	-113.31	6057.31		19192.07		39.13%
1	0.5	**Model 3**	4425.77	1733.36	-110.86	6048.27	**-0.15%**	15423.87	**-19.63%**	39.17%
1	0.75	**Model 2**	4461.83	1594.94	-117.64	5939.14		19598.74		35.75%
1	0.75	**Model 3**	4459.78	1593.81	-115.06	5938.53	**-0.01%**	14691.37	**-25.04%**	35.74%
1	1	**Model 2**	4482.26	1480.22	-122.00	5840.49		19953.74		33.02%
1	1	**Model 3**	4487.62	1478.71	-118.66	5847.68	**0.12%**	14106.58	**-29.30%**	32.95%
1	1.25	**Model 2**	4499.98	1385.77	-125.60	5760.15		20220.53		30.80%
1	1.25	**Model 3**	4511.36	1383.40	-121.73	5773.03	**0.22%**	13622.31	**-32.63%**	30.66%
1	1.5	**Model 2**	4512.04	1306.52	-128.15	5690.41		20506.63		28.96%
1	1.5	**Model 3**	4529.92	1302.45	-124.03	5708.34	**0.32%**	13219.59	**-35.54%**	28.75%
0.5	1	**Model 2**	4803.53	478.80	-97.69	5184.64		15744.14		9.97%
0.5	1	**Model 3**	4790.33	476.36	-95.93	5170.76	**-0.27%**	12549.33	**-20.29%**	9.94%
0.75	1	**Model 2**	4645.65	939.58	-110.98	5474.26		17784.67		20.23%
0.75	1	**Model 3**	4639.49	936.20	-108.34	5467.35	**-0.13%**	13121.52	**-26.22%**	20.18%
1.25	1	**Model 2**	4340.68	2061.19	-130.48	6271.38		21682.81		47.49%
1.25	1	**Model 3**	4350.03	2059.31	-126.71	6282.63	**0.18%**	15322.78	**-29.33%**	47.34%
1.5	1	**Model 2**	4219.25	2662.41	-136.79	6744.87		23199.08		63.10%
1.5	1	**Model 3**	4234.64	2659.52	-132.42	6761.75	**0.25%**	16353.95	**-29.51%**	62.80%

V. Conclusion

A novel optimization model for the calculation of the water value of a hydropower plant has been presented in this paper. The model considers sales of both energy and reserve. The novelty of the model lies in that it considers the influence of the hydropower producer on the clearing price of the reserve market. The model has been used to analyse the impact of the price-making behaviour on the overall economical and scheduling results of an existing hydropower plant, which is currently operating in the Spanish electricity market. The results obtained in the paper indicate that the plant's profit might increase by up to 0.12 % if the plant's water values were computed considering the producer's price-making ability in the reserve market. This increase is modest compared to the uncertainty existing in the day-ahead scheduling. However, the results also indicate that the water spillage significantly decreases if the producer's price making ability in the reserve market is considered to compute the plant's water value. This last result may have important implications for the plant's operation, especially when the reservoir is also used for the purpose of flood control, as the one used as case study in the paper.

The results obtained in the paper assuming the participation of the same hydropower plant in other synthetically generated reserve markets are analogous to those obtained for the Spanish reserve market. The profit increase is modest in all cases, compared to the uncertainty existing in the day-ahead scheduling, and becomes even negative when the slope of the residual demand curve or the price of the reserve market decreases. However, the water spillage is always significantly lower when the producer's price-making ability in the reserve market is considered to compute the plant's water value.

We believe that the presented model is well suited for detailed multi-market studies of hydropower systems with one or a few reservoirs and with inherit non-convexities in the model formulation. Moreover, it can be used to benchmark the scheduling policies from state-of-the-art linear models, and to quantify the approximation errors in those. The results presented in the paper can be useful for hydropower companies to evaluate whether or not to upgrade the optimization tools used to compute the water value. The formulation presented in the paper might be helpful to undertake such an upgrade.

Finally, we propose as future lines of research the consideration of risk-aversion constraints for the computation of the water value, as well as other energy and ancillary services markets, such as the auction intraday markets and the manual FRR market of the Spanish power system, and the comparison to other approaches not based on the classical splitting between the medium- and short-term generation scheduling as the one suggested in [41] and [42].

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