Hydro energy systems management in Portugal: profit-based evaluation of a mixed-integer nonlinear approach

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Abstract

In this paper, a novel mixed-integer nonlinear approach is proposed to solve the short-term hydro scheduling problem in the day-ahead electricity market, considering not only head-dependency, but also start/stop of units, discontinuous operating regions and discharge ramping constraints. Results from a case study based on one of the main Portuguese cascaded hydro energy systems are presented, showing that the proposed mixed-integer nonlinear approach is proficient. Conclusions are duly drawn.

Keywords: Short-term hydro scheduling; Mixed-integer nonlinear programming; Cascaded reservoirs; Head-dependency

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1. Introduction

The use of renewable energies has been increasing in the last decade worldwide [1], particularly in European countries such as Denmark [2,3], Ireland [4], and Spain [5]. Concerning renewable energies, hydro energy is currently one of the priorities in the Portuguese energy policy. Under this energy policy, the optimal management of hydro energy systems is of crucial importance [6], as occurs for instance in Norway [7].

In this paper, the short-term hydro scheduling (STHS) problem of a head-sensitive cascaded hydro energy system is considered. In hydro plants with a small storage capacity available, also known as run-of-the-river hydro plants, operating efficiency may become sensitive to the head: head change effect [8–9].

In the Portuguese energy system there are several cascaded hydro energy systems formed by many but small reservoirs. This is the situation for example in the Douro River, which represents about two-thirds of the total hydroelectric power generation in the country.

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The existing hydro plants in the Douro River are of the run-of-the-river type, where the head change effect plays a major role. Hence, it is necessary to consider head-dependency on STHS. The head change effect coupled with the cascaded hydraulic configuration augments the problem complexity and dimension.

In the STHS problem a time horizon of one day to one week is considered, usually divided into hourly intervals. Hence, the STHS problem is treated as a deterministic one. Where the problem includes stochastic quantities, such as inflows to reservoirs or energy prices, the corresponding forecasts are used.

In a deregulated environment, a hydro generating company (H-GENCO) is usually an entity owning generation resources and participating in the electricity market with the ultimate goal of maximizing profits, without concern of the energy system, unless there is an incentive for it. A day-ahead electricity market based on a pool is considered in this paper.

The optimal management of the water available in the reservoirs for power generation, regarding future operation use, delivers a self-schedule and represents a major advantage for the H-GENCO to face competitiveness given the economic stakes involved. Based on the self-schedule, the H-GENCO is able to submit bids with rational support to the electricity market. Thus, for deregulation applications, STHS solution is important as a decision support for developing bidding strategies in the market [10], guided by the forecasted energy prices, and a more realistic modeling is crucial for surviving nowadays competitive framework.

Dynamic programming (DP) is among the earliest methods applied to the STHS problem [11]. Although DP can handle the nonconvex, nonlinear characteristics present in the hydro model, direct application of DP methods for cascaded hydro energy systems is impractical due to the well-known DP curse of dimensionality.

Artificial intelligence techniques have also been applied to the STHS problem [12–15]. However, due to the heuristics used in the search process only sub-optimal solutions can be reached.

A natural approach to STHS is to model the energy system as a network flow model, because of the underlying network structure subjacent in cascaded hydro energy systems [16]. For cascaded hydro energy systems, as there are water linkage and electric connections among plants, the advantages of the network flow technique are salient.

Hydroelectric power generation characteristics are often assumed as linear or piecewise linear in hydro scheduling models. Accordingly, the solution procedures are based on linear programming (LP) or mixed-integer linear programming (MILP).

LP is a well-known optimization method and standard software can be found commercially. MILP is very powerful for mathematical modeling and is applied successfully to solve large-size scheduling problem in power energy systems. Hence, MILP is becoming often used for STHS [17–19], where binary variables allow modeling of start-up costs and discrete hydro unit-commitment constraints. The number of start-ups of hydro units should be low, since frequent start-ups shorten the lifetime of the units as a result of mechanical stress. Thus, start-up costs are usually introduced to discourage frequent start-ups. The five aspects causing start-up costs are [20]:

(i) Loss of water during maintenance.

(ii) Wear and tear of the windings due to temperature changes during the start-up.

(iii) Wear and tear of mechanical equipment during the start-up.

(iv) Malfunctions in the control equipment during the start-up.

(v) Loss of water during the start-up.

The start-up costs are mainly caused by increased maintenance of windings and mechanical equipment and by malfunctions in the control equipment. The cost of lost water is usually small.

The LP and MILP approaches applied to the STHS problem have some drawbacks.

On the one hand, LP typically considers that hydroelectric power generation is linearly dependent on water discharge, thus ignoring head-dependency to avoid nonlinearities. This is not appropriate for a realistic modeling of run-of-the-river hydro plants.

On the other hand, the discretization of the nonlinear dependence between power generation, water discharge and head, used in MILP to model head variations, augment the computational burden required to solve the STHS problem. For instance, the optimal solution reported in [17] required 22 minutes of CPU time, on a 400-MHz-based processor with 500 MB of RAM. Furthermore, methods based on successive linearization in an iterative scheme depend on the expertise of the operator to properly calibrate the parameters. For instance, the selection of the best under-relaxation factor in [18] is empirical and case-dependent, rendering some ambiguity to these methods. Sequential MILP could be an interesting approach, but the computational complexity may represent a drawback.

Hydro scheduling is in its nature a nonlinear optimization problem. A nonlinear model has advantages compared with a linear one. A nonlinear model expresses hydroelectric power generation characteristics more accurately and head-dependency on STHS can be taken into account.

In earlier studies [8,9], the use of the nonlinear model in some case studies leads to a result that exceeds by at least three percent what is obtained by a linear model, requiring a negligible extra computation time.

However, the nonlinear model cannot avoid water discharges at forbidden zones, and ignoring the start/stop of units may give schedules unacceptable from an operation point of view. Moreover, it is important to notice that a minor change in the energy price may give a significant change in the water discharge, and consequently in the power generation of plants. Therefore, ramp rate of water discharge should be included in the constraints to keep a lesser and steady head variation, which is particularly important for reservoirs with a task of navigation.

Hence, mixed-integer nonlinear programming (MINLP) is proposed in this paper for solving the STHS problem in the day-ahead electricity market. Indeed, MINLP is a state-of-the-art research in the subject of STHS. Solving a MINLP version of the STHS problem is much harder than the NLP version, since the new binary variables required moves the problem to another level of complexity.

The new contributions of the proposed MINLP approach are to deal in the same optimization model three STHS characteristics:

(i) Start/stop of units.

(ii) Discontinuous operating regions.

(iii) Discharge ramping constraints.

The paper is structured as follows. Section 2 presents the mathematical formulation of the STHS problem. Section 3 develops the proposed method for solving the STHS problem considering head dependence, discharge ramping constraints and start/stop of units. Section 4 presents a case study, illustrating the numerical simulation results. Section 5 provides error analysis and, finally, Section 6 provides conclusions.

Nomenclature

I, i	set and index of reservoirs
K, k	set and index of hours in the time horizon
λ_k	forecasted energy price in hour *k*
p_{ik}	power generation of plant *i* in hour *k*
SU_i	start-up cost of plant *i*
y_{ik}	binary variable which is equal to 1 if plant *i* is started-up at beginning of hour *k*
z_{ik}	binary variable which is equal to 1 if plant *i* is shut-down at beginning of hour *k*
a_{ik}	inflow to reservoir *i* in hour *k*
M_i	set of upstream reservoirs to reservoir *i*
q_{ik}	water discharge by reservoir *i* in hour *k*
s_{ik}	water spillage by reservoir *i* in hour *k*
h_{ik}	head of plant *i* in hour *k*
η_{ik}	power efficiency of plant *i* in hour *k*
u_{ik}	binary variable which is equal to 1 if plant *i* is on-line in hour *k*
R_i	discharge ramping limit of plant *i*
$\overline{v}_i, \underline{v}_i$	water storage limits of reservoir *i*
$\overline{q}_i, \underline{q}_i$	water discharge limits of plant *i*
$\overline{p}_i, \underline{p}_i$	power generation limits of plant *i*
v_{i0}	initial water storage of reservoir *i*
A	constraint matrix
$\overline{b}, \underline{b}$	upper and lower bound vectors on constraints
x	vector of decision variables
$\overline{x}, \underline{x}$	upper and lower bound vectors on decision variables

2. Problem formulation

The STHS problem can be stated as to find out the water discharges, the water storages, and the water spillages, for each reservoir *i* at all scheduling time periods *k* that maximizes (or minimizes) a performance criterion subject to all hydraulic constraints. Additionally, the commitment decision, u_{ik}, is ascertained.

2.1 Objective function

In this paper, the objective function to be maximized is expressed as:

$$\sum_{i=1}^{I} \sum_{k=1}^{K} \left(\lambda_k \, p_{ik} - SU_i \, y_{ik} \right) \tag{1}$$

In (1), the first term is related to the revenues of each plant *i* in the hydro energy system during the short-term time horizon, whereas the second term represents the start-up costs, which is a new contribution to earlier studies [8,9].

The future value of the water stored in the reservoirs is not considered in (1), since the water storage in the reservoirs in the last period is fixed. An appropriate representation when this term is explicitly taken into account can be seen for instance in [21]. The storage targets for the short-term time horizon can be established by medium-term planning studies.

2.2 Hydro constraints

The hydro constraints are of two kinds: equality constraints and inequality constraints or simple bounds on the decision variables.

The water balance equation for each reservoir is formulated as:

$$v_{ik} = v_{i,k-1} + a_{ik} + \sum_{m \in M_i} (q_{mk} + s_{mk}) - q_{ik} - s_{ik} \quad \forall\, i \in I, \quad \forall\, k \in K \tag{2}$$

assuming that the time required for water to travel from a reservoir to a reservoir directly downstream is less than the one hour period, due to the small distance between consecutive reservoirs. This is a realistic assumption for the hydro energy system considered.

The head of a hydro plant *i* measures the difference between the forebay elevation and the tailrace elevation. Therefore, it can be expressed as a function of its reservoir storage $v_{f(i)\,k}$, and the immediate downstream reservoir storage $v_{t(i)\,k}$ [18]:

$$h_{ik} = h_{ik}\,(v_{f(i)\,k}, v_{t(i)\,k}) \quad \forall\, i \in I, \quad \forall\, k \in K \tag{3}$$

If the tailrace elevation is considered constant, this relationship can be simplified [18]:

$$h_{ik} = h_{ik}(v_{f(i)k}) \quad \forall\, i \in I, \quad \forall\, k \in K \tag{4}$$

so that the head depends only on the storage of the upstream reservoir. The relationship (4) can be considered adequate for the Spanish energy system [18]. Instead, the relationship (3) can be considered adequate for the Portuguese energy system [8,9], where reservoirs are usually small and close to each other. Hence, in this paper, the tailrace elevation is not considered constant, depending on the storage of the immediately downstream reservoir.

Power generation is considered a function of water discharge and hydro power efficiency:

$$p_{ik} = q_{ik}\, \eta_{ik}(h_{ik}) \quad \forall\, i \in I, \quad \forall\, k \in K \tag{5}$$

Hydro power efficiency is expressed as the output-input ratio, depending on the head. Hence, the power output of a hydro plant depends on the water discharge, the efficiency and the head.

Water storage has lower and upper bounds, given by:

$$\underline{v}_i \le v_{ik} \le \bar{v}_i \quad \forall\, i \in I, \quad \forall\, k \in K \tag{6}$$

Water discharge has lower and upper bounds, given by:

$$u_{ik}\, \underline{q}_i \le q_{ik} \le u_{ik}\, \bar{q}_i \quad \forall\, i \in I, \quad \forall\, k \in K \tag{7}$$

As a new contribution to earlier studies [8,9], the commitment decision of each hydro plant is considered. Hence, the binary variable, u_{ik}, is equal to 1 if plant *i* is on-line in hour *k*, otherwise is equal to 0. Also, as a new contribution to earlier studies [8,9], discharge ramping constraints are considered, given by:

$$q_{ik} - R_i \le q_{i,k+1} \le q_{ik} + R_i \quad \forall\, i \in I, \quad \forall\, k \in K \tag{8}$$

which may be imposed due to requirements of navigation, environment, and recreation.

A null lower bound for water spillage is considered, given by:

$$s_{ik} \ge 0 \quad \forall\, i \in I, \quad \forall\, k \in K \tag{9}$$

thus, water spillage can occur when without it the water storage exceeds its upper bound, so spilling is necessary due to safety considerations. The spillage effects were considered in [22].

The following constraints:

$$y_{ik} - z_{ik} = u_{ik} - u_{i,k-1} \quad \forall\, i \in I, \quad \forall\, k \in K \tag{10}$$

are necessary to model the start-up and shut-down status of the plants. Although variables z_{ik} may seem superfluous since they only appear in (10), extensive numerical simulations have proven their ability in considerably reducing computation time [17].

The initial water storages and inflows to reservoirs are assumed known. The H-GENCO analyzed in this paper is considered to be a price-taker, i.e., it does not have market power. Therefore, energy prices λ_k in (1) are also assumed known, as in [17, 19].

To consider uncertainty on energy prices requires a stochastic programming approach. A scenario tree should be adequately constructed and trimmed, which is outside the scope of this paper since the STHS problem is considered as a deterministic one. Nevertheless, an appropriate representation when market uncertainty is explicitly taken into account via price scenarios can be seen for instance in [18, 23].

3. Proposed approach

The MINLP problem can be stated as to maximize:

$$F(x) \tag{11}$$

subject to:

$$\underline{b} \le A\,x \le \overline{b} \tag{12}$$

$$\underline{x} \le x \le \overline{x} \tag{13}$$

$$x_j \text{ integer} \quad \forall\, j \in J \tag{14}$$

In (11), the function $F(\cdot)$ is a nonlinear function of the vector x of decision variables. The decision variables are the hourly commitment variables of the plants and the water discharges. Equality constraints are defined by setting the lower bound equal to the upper bound, i.e. $\underline{b} = \overline{b}$. The variables x_j are restricted to have 0/1 values. The lower and upper bounds for water discharge imply new inequality constraints that will be rewritten into (12).

Power generation is considered a nonlinear function of water discharge and water storage, as in [8,9], given by:

$$p_{ik} = \alpha_i\, \beta_{f(i)}\, q_{ik}\, v_{f(i)k} - \alpha_i\, \beta_{t(i)}\, q_{ik}\, v_{t(i)k} + \chi_i\, q_{ik} \quad \forall\, i \in I, \quad \forall\, k \in K \tag{15}$$

A major advantage of our approach is to consider the head change effect in a single function (15) of water discharge and water storage that can be used in a straightforward way, instead of deriving several curves for different heads. Parameter α is given by the values for efficiency and head, while parameter β is given by the values for water level and storage. Hence, efficiency and head are also implicitly considered in (15), alongside water discharge and water storage.

The parameters given by the product of α's by β's are of crucial importance for the behavior of head-sensitive reservoirs in a hydro energy system, setting optimal reservoirs storage trajectories in accordance to their relative position in the cascade. The parameter χ_i, which is related to the linear term of the objective function, is also determined only by physical data defining the hydro energy system. Alternative physical data resulting in different values for these parameters were considered in one of our earlier studies [24]. In this paper, only real data from one of the main Portuguese cascaded hydro energy systems is used.

The proposed MINLP approach considers not only head-dependency (15), but also start/stop of units (1), discontinuous operating regions (7), and discharge ramping constraints (8). Therefore, more realistic and feasible results are attainable using the proposed MINLP approach, compared to earlier studies [8,9].

A starting point given by a MILP approach is considered, and afterwards an enhanced objective function value is checked using the proposed MINLP approach. In our case study, the proposed approach always arrives at convergence to a better solution.

4. Case study

The proposed MINLP approach has been applied on one of the main Portuguese cascaded hydro energy systems. Our model has been developed and implemented in MATLAB and solved using the optimization solver package Xpress-MP, which solves large-scale mixed-integer quadratic programming problems, with simplex or barrier solvers. Hence, the proposed MINLP approach uses general software and no algorithmic work is performed. The numerical testing has been performed on a 600-MHz-based processor with 256 MB of RAM.

4.1 Input data

The realistically-sized hydro energy system has seven cascaded reservoirs and is shown in Fig. 1. Table 1 shows the data of these plants.

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The hydro plants numbered in Fig. 1 as 1, 2, 4, 5 and 7 are run-of-the-river hydro plants. The hydro plants numbered as 3 and 6 are storage hydro plants. Inflow is considered only on reservoirs 1 to 6. The final water storage in the reservoirs is constrained to be equal to the initial water storage. The hydro units start-up costs have been estimated as a function of its nominal output power, $SU_i = \overline{p}_i \times 2.5$, as in [18]. Also, forbidden zones for the hydro units are considered using (7). These zones result from mechanical vibrations, cavitation, and low efficiency level [25].

The time horizon is one day divided into 24 hourly intervals. The energy price profile considered over the short-term time horizon is shown in Fig. 2 ($ is a symbolic economic quantity). The energy price values are based on real market operation.

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The competitive environment coming from the deregulation of the electricity markets brings energy prices uncertainty, placing higher requirements on forecasting. A good price forecasting tool reduces the risk of under/over estimating the profit of the H-GENCO and provides better risk management. In the short-term, a generating company needs to forecast energy prices to derive its bidding strategy in the market and to optimally schedule its energy resources [26].

Price forecasting has become in recent years an important research area in electrical engineering, and several techniques have been tried out in this task. In general, hard and soft computing techniques could be used to predict energy prices. The hard computing techniques include auto regressive integrated moving average (ARIMA) [27] and wavelet-ARIMA [28] models. The soft computing techniques include neural networks [29] and hybrid approaches [30–32]. These energy prices are considered as deterministic input data for our STHS problem.

4.2 Result analysis

A thorough comparison of MINLP with NLP and MILP results is presented thereafter, highlighting the contributions modeled in this paper. The MILP is derived from MINLP, assuming that hydroelectric power generation is linearly dependent on water discharge.

Firstly, the proposed MINLP approach is compared with a NLP approach. The start-up costs and discharge ramping constraints are initially not considered in the MINLP approach. Both approaches consider head-dependency. Hence, as a new contribution to earlier studies [8,9], the water discharges at forbidden zones are avoided, namely between 0 and $\underline{q}_i$.

The storage trajectories of the reservoirs are shown in Fig. 3. The discharge profiles for the reservoirs are shown in Fig. 4. The solid lines denote MINLP results while the dashed lines denote NLP results.

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The comparison of MINLP with NLP results, shown in Fig. 3, reveals almost identical storage trajectories for both approaches. Nevertheless, some different behavior is possible to be observed for the first and second reservoirs, at a neighborhood of 9h.

The comparison of MINLP with NLP results, shown in Fig. 4, reveals that the NLP approach cannot avoid water discharges at forbidden zones, clearly observable for the first and second reservoirs at a neighborhood of 15h. At a neighborhood of 15h, water discharges are between 0 and $\underline{q}_i$ with the NLP approach, therefore inside the forbidden zone, but are above $\underline{q}_i$ with the MINLP approach. Hence, the NLP solution violates the forbidden zone constraints, and may give schedules unacceptable from an operation point of view.

The main numerical results are summarized in Table 2. Although the profit may be slightly higher with the NLP approach (0.02%), it should be noted that the results obtained using the MINLP approach are more realistic and feasible, since water discharges at forbidden zones are avoided, i.e., the water discharges at forbidden zones are scheduled at slightly less profitable hours using our MINLP approach.

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Secondly, the proposed MINLP approach is compared with a MILP approach. The start-up costs and discharge ramping constraints are initially not considered in the MILP approach. Both approaches consider discontinuous operating regions. The storage trajectories of the reservoirs are shown in Fig. 5. The discharge profiles for the reservoirs are shown in Fig. 6. The solid lines denote MINLP results while the dashed lines denote MILP results.

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The comparison of MINLP with MILP results, shown in Fig. 5, reveals the influence of considering the head change effect in the behavior of the reservoirs. The upstream reservoir should operate at a suitable high storage level in order to benefit the power generation efficiency of its associated plant, due to the head change effect.

Hence, the storage trajectory of the upstream reservoir is pulled up using the MINLP approach. Instead, the storage trajectory of the last downstream reservoir is pulled down using the MINLP approach, thereby improving the head for the immediately upstream reservoirs. Hence, the different behavior between MILP and MINLP is explained by the head change effect.

The comparison of MINLP with MILP results, shown in Fig. 6, reveals that the water discharge changes more quickly from the minimum value to the upper value in the MILP results than in the MINLP results, also due to the head change effect.

As a new contribution to earlier studies [8,9], start-up costs are included in the objective function, which implies a different behavior of the reservoirs: once a hydro unit is committed, it tends to remain on-line during more hours, avoiding frequent start-ups. Also, as a new contribution to earlier studies [8,9], discharge ramping constraints enhance the operational condition of reservoirs and units, keeping a lesser and steady head variation.

The main numerical results shown in Fig. 5 and Fig. 6 are summarized in Table 3. Although the average water discharge is as expected the same for both optimization methods, the average storage is superior with the proposed MINLP approach, due to the consideration of the head change effect. Thus, regardless of the price scenario considered, with the proposed MINLP approach a higher total profit for the H-GENCO is attainable, about 4.3%. Moreover, the additional CPU time required is acceptable.

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If the MILP approach considers also start-up costs and discharge ramping constraints, the corresponding total profit is lower, 707.82 k$, and the CPU time increases to 5.20 seconds. In order to model head variations in MILP, the discretization of the nonlinear dependence between power generation, water discharge and head is required. However, such discretization augments the computational burden required to solve the STHS problem. For instance, the optimal solution reported in [17] required 22 minutes of CPU time, on a 400-MHz-based processor with 500 MB of RAM, using CPLEX.

A major advantage of our approach is to consider the head change effect in a single function of water discharge and water storage that can be used in a straightforward way, instead of deriving several curves for different heads. In our paper, the optimal solution requires only 9.26 seconds of CPU time, on a 600-MHz-based processor with 256 MB of RAM, using Xpress-MP, and considering head-dependency, discontinuous operating regions, start-up costs and discharge ramping constraints.

Our novel MINLP approach is both accurate and computationally acceptable, providing better results for head-sensitive cascaded hydro energy systems. Hence, the proposed MINLP approach does indeed contribute to making STHS problem in the day-ahead electricity market better. However, the computational burden could increase considerably for larger energy systems, as the number of binary variables increases, which may represent a drawback of the proposed MINLP approach.

5. Error analysis

An error analysis is necessary to evaluate the accuracy of the approaches presented in this paper. The approaches based on NLP and MINLP require the application of two linearizations to model the STHS problem, considering a cascaded hydro energy system. In fact, these linearizations induce some errors that can be treated and evaluated in order to observe the degree of inaccuracy committed by their use.

The nonlinear objective function is achieved by means of two linearizations: the first of them, efficiency as a function of head, is acceptable; the second one, water level as a function of water storage, implies reservoirs with vertical walls, which however is a good approximation for the run-of-the-river reservoirs, due to its small storage capacity, as our data have shown for our case study.

The average errors associated with the linearization curves, efficiency vs. head and water level vs. water storage, are presented in Table 4.

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According to Table 4, it can be seen that the average errors are relatively small, concerning the cascaded hydraulic configuration studied. Hence, the results are realistic for the STHS problem, ensuring the physical and technical conditions of the hydro plants.

A discussion regarding solution convergence is presented thereafter. We consider a starting point given by the MILP approach, and afterwards we check for an enhanced objective function value using the proposed MINLP approach. In our case study we always arrive at convergence to a better solution. Also, it should be noted that the parameters in MINLP are not related to the solution procedure. Instead, they are determined only by physical data defining the hydro energy system.

6. Conclusions

A novel mixed-integer nonlinear approach is proposed to solve the STHS problem in the day-ahead electricity market, considering not only head-dependency, but also start/stop of units, discontinuous operating regions and discharge ramping constraints. A major advantage of our approach is to consider the head change effect in a single function of water discharge and water storage that can be used in a straightforward way, instead of deriving several curves for different heads. The new contributions to earlier studies are threefold: 1) binary variables are used to model the on-off behavior of the hydro plants, avoiding water discharges at forbidden zones; 2) start-up costs are included in the objective function to discourage frequent start-ups; 3) ramp rate of water discharge is included in the constraints to keep a lesser and steady head variation. A thorough comparison with NLP and MILP approaches is carried out in this paper, clearly demonstrating the advantages of the proposed MINLP approach. The results obtained by the proposed MINLP approach are more realistic and feasible, while assuring an acceptable computation time.

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Figure captions

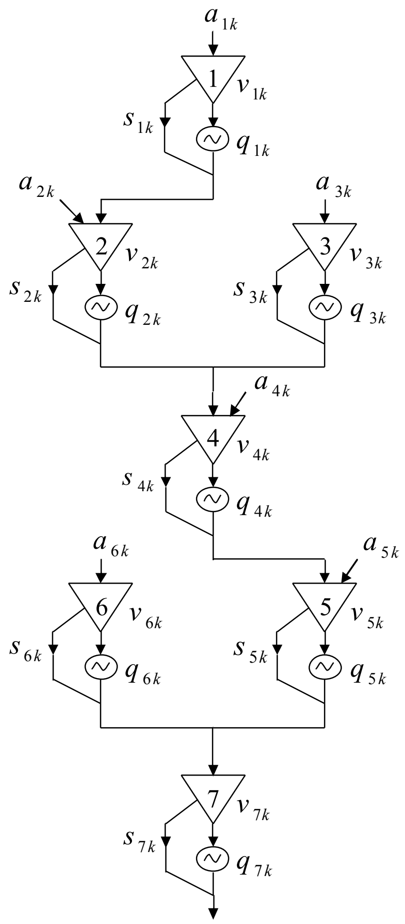

Fig. 1. Hydro energy system with seven cascaded reservoirs. The hydro plants numbered as 1, 2, 4, 5 and 7 are run-of-the-river hydro plants, while the hydro plants numbered as 3 and 6 are storage hydro plants.

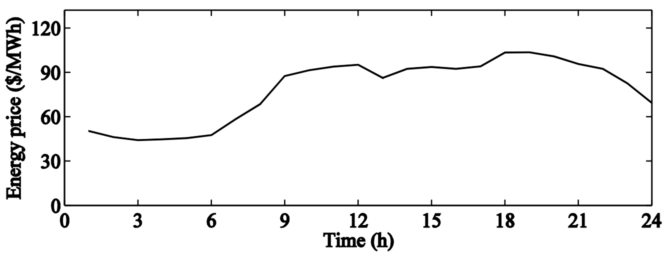

Fig. 2. Energy price profile considered over the short-term time horizon, where $ is a symbolic economic quantity.

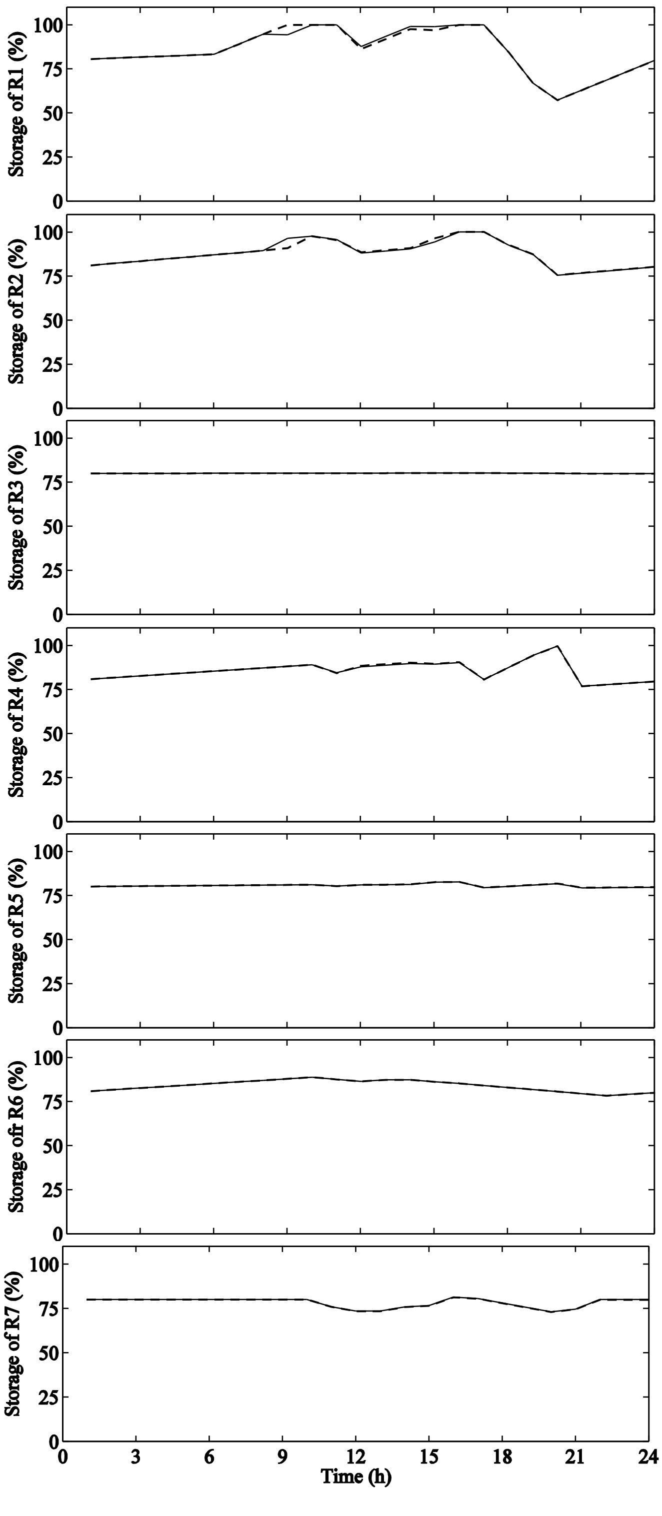

Fig. 3. Storage trajectories of the reservoirs considering the proposed MINLP approach and a NLP approach. The solid lines denote MINLP results while the dashed lines denote NLP results.

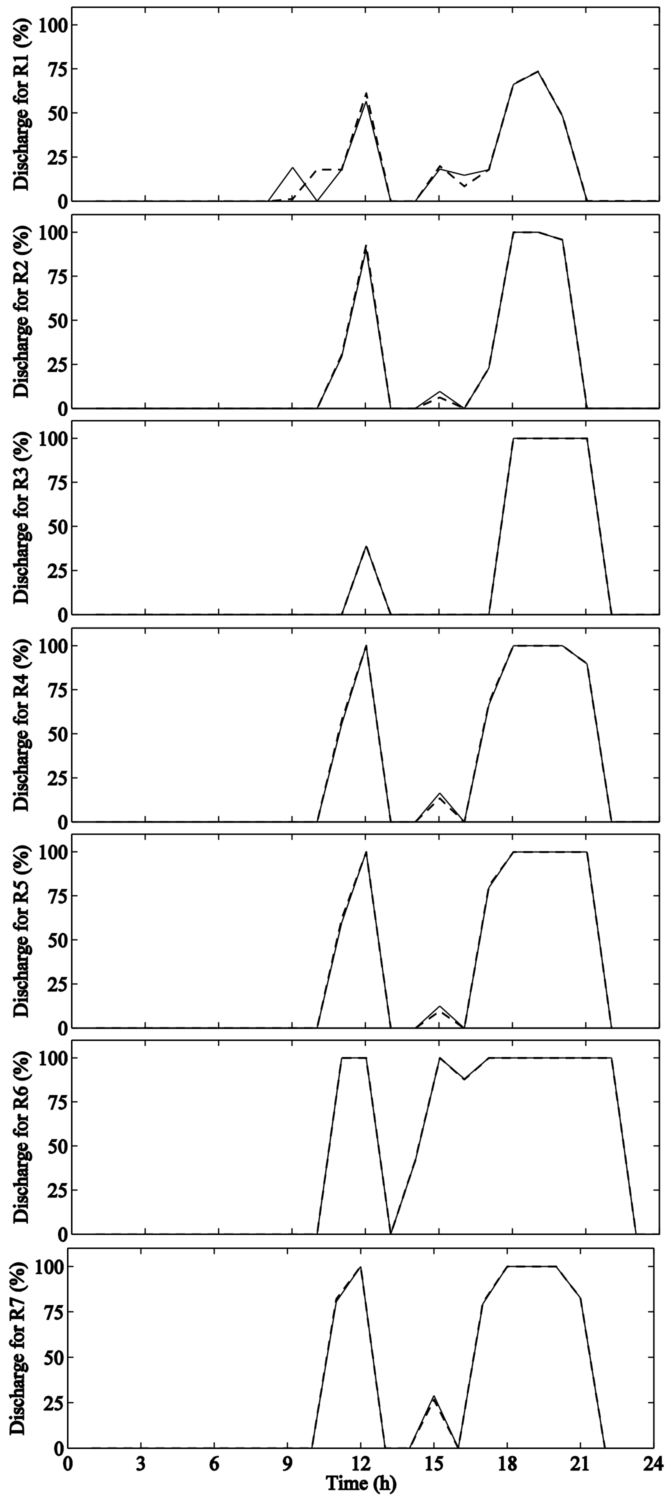

Fig. 4. Discharge profiles for the reservoirs considering the proposed MINLP approach and a NLP approach. The solid lines denote MINLP results while the dashed lines denote NLP results.

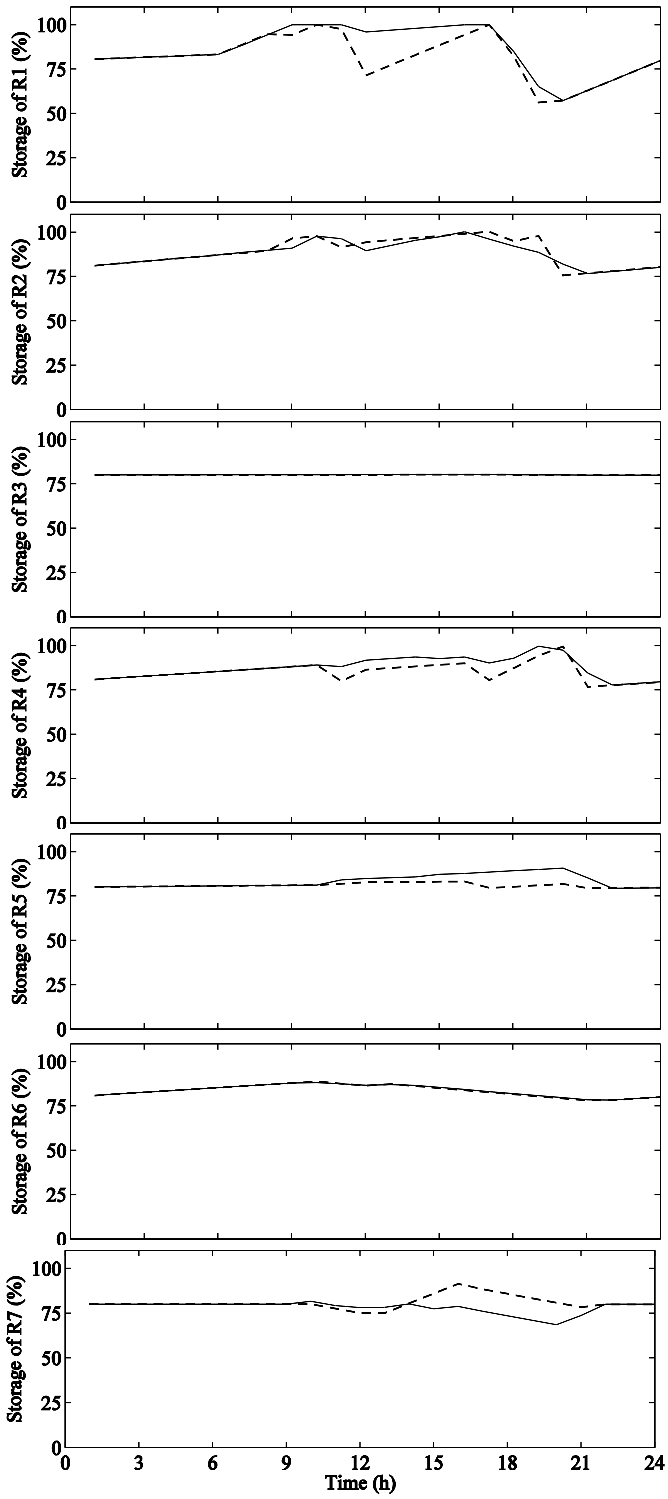

Fig. 5. Storage trajectories of the reservoirs considering the proposed MINLP approach and a MILP approach. The solid lines denote MINLP results while the dashed lines denote MILP results.

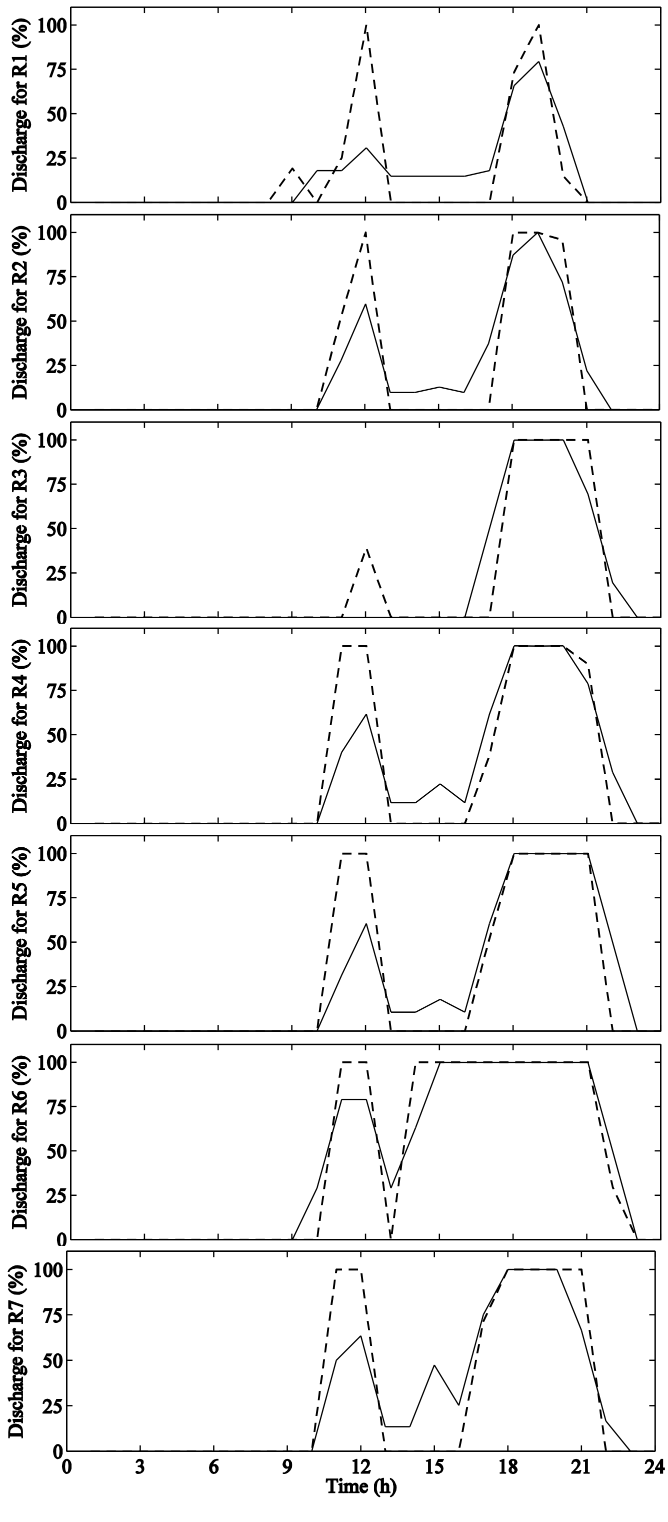

Fig. 6. Discharge profiles for the reservoirs considering the proposed MINLP approach and a MILP approach. The solid lines denote MINLP results while the dashed lines denote MILP results.

Tables

Table 1

Hydro data

#	$\underline{v}_i$ (hm^3)	$\bar{v}_i$ (hm^3)	v_{i0} (hm^3)	$\underline{p}_i$ (MW)	$\bar{p}_i$ (MW)	$\underline{q}_i$ (m^3/s)	$\bar{q}_i$ (m^3/s)
1	5.18	12.94	10.35	28.00	188.08	168.13	1144.50
2	5.32	13.30	10.64	29.99	237.14	104.70	1080.00
3	39.00	97.50	78.00	10.67	60.00	3.00	16.40
4	4.80	12.00	9.60	24.99	185.99	104.67	900.00
5	4.40	11.00	8.80	29.99	201.02	93.23	881.31
6	36.89	58.38	46.70	39.99	134.02	94.99	326.34
7	8.60	21.50	17.20	19.99	117.01	182.83	1356.51

Table 2

Comparison of MINLP with NLP results; ramping and start-up are not used for the MINLP

Method	Average Discharge (%)	Average Storage (%)	Total Profit ($\$ \times 10^3$)	CPU (s)
NLP	25.00	83.08	751.38	1.48
MINLP	25.00	83.08	751.21	3.25

Table 3

Comparison of MINLP with MILP results; ramping and start-up are not used for the MILP

Method	Average Discharge (%)	Average Storage (%)	Total Profit ($\$ \times 10^3$)	CPU (s)
MILP	25.00	83.08	714.38	1.75
MINLP	25.00	83.86	745.31	9.26

Table 4

Linearization errors

Linearization	Average Error (%)	Std. Error (%)
Efficiency vs. Head	0.54	0.16
Water Level vs. Water Storage	0.12	0.08