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Ensemble of Markovian stochastic dynamic programming models in different time scales for long term hydropower scheduling

R.O.C. Scarcelli [a,*], M.S. Zambelli [b], S. Soares [b], A.A.F.M. Carneiro [c]

[a] Federal Institute of São Paulo (IFSP), São João da Boa Vista, SP, Brazil
[b] State University of Campinas (UNICAMP), Campinas, SP, Brazil
[c] University of São Paulo (USP), São Carlos, SP, Brazil

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ABSTRACT

This paper presents a new approach for long term hydropower scheduling. In opposition to the standard Markovian stochastic dynamic programming approach, where monthly inflows are modeled according to probability distribution functions, conditioned to some occurrence of inflow in the previous month, in the proposed approach the monthly inflows are aggregated in different time scales and then submitted to the Markovian model. The discharge decisions are then calculated by a deterministic model that optimizes the problem for one year ahead according to inflows provided by a combination of each Markovian model. Tests were conducted on hypothetical single-reservoirs hydrothermal systems using data from four real Brazilian hydro plants, with distinct hydrological regimes. The performance of the proposed method was evaluated through simulation, using the historical inflow data, in comparison with the standard Markovian model. The results have shown that the proposed approach has provided spillage reduction and increase on hydro productivity as well as power generation, which incurred in up to 2.1% reduction in operational costs.

1. Introduction

The idea of controlling reservoir's storage is connected to the human development since ancient times [1]. After 1940's, accelerated by the second war, a large advance on dam management was published emerging from the theory of sequential decisions [2].

Later on, many contributions were proposed and the most accepted technique, until nowadays, to solve long term hydropower scheduling, LTHS, was proposed in 1976. Stochastic dynamic programming, SDP, is a closed-loop control policy that aims to determine optimal decisions for a range of discrete states of the system. The main limitation of SDP is the so-called "curse of dimensionality" as the computational effort increases exponentially with the number of state variables [3].

As scheduling problems were getting more challenging (power system growth, diversification of power sources and market issues involved) and taking advantage of technological advances, several improvements were developed over the SDP theory.

In Ref. [4] general uses of dynamic programming, DP, and classical modeling are presented. Later on, some adaptations to bypass the "curse of dimensionality" [12] and to solve instability problems [13–15] were implemented. Different approaches and heuristics methods, associated with DP [7,10] were also considered for different problems. Intelligent systems with neural networks were also incorporated to DP in Refs. [5,6,8,9,11]. A deep resume of a great number of DP based techniques for solving reservoirs operation problems is presented in Ref. [16]. Streamflow prediction models were also tested in substitution of classical statistical models [17].

Annual inflow prediction has been proposed and tested in a framework of predictive control modeling [18]. The comparison between this method and the standard one, Markovian stochastic dynamic programming, MSDP, has shown expressive improvements, indicating that annual inflow models can provide better information for optimal monthly decision-making problems. The reason is that it might be more important to foresee the total inflow for the next year, which includes the next wet season, then to foresee the inflow of the next month [20–24], since optimal decision-making aims to maximize hydro generation but at the same time distribute it on time so that thermal generation costs be as flat as possible within the planning horizon. The extension of this idea to SDP is possible and has shown promising results [19].

* Corresponding author.
E-mail addresses: scarcelli@ifsp.edu.br (R.O.C. Scarcelli), monica@cose.fee.unicamp.br (M.S. Zambelli), dino@cose.fee.unicamp.br (S. Soares), adriano@eesc.usp.br (A.A.F.M. Carneiro).

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This paper proposes a new approach to solve LTHS problems based on a nested composition of MSDP models which results, from the aggregation of monthly inflows up to one year on different time scales. Decision-making at each month is then determined as the optimal decision of the first monthly stage of a deterministic non-linear optimization model that solves the LTHS one year ahead, in monthly steps, with inflows provided by the MSDP models. It is possible to implement the proposed technique in a larger system with more than one hydropower plant using the equivalent reservoir technique [4]. In this paper only single reservoir systems were considered to clearly identify the differences between the classical methods and the proposed one.

This paper is structured as follows. Section 2 presents the LTHS model with a brief explanation of the SDP modeling and main variables description. The proposed method is also explained and discussed, along with the motivation and some characteristics of the hydro data that support the main idea. Section 3 presents the case studies and results. Finally, Section 4 summarizes the main contribution and takes some conclusions.

2. Problem formulation

The LTHS for single-reservoir hydropower systems can be formulated as the following stochastic optimization problem:

$$\text{Objective: } \alpha_1(x_0, y_0) = \min_q E_y \left\{ \sum_{\substack{t=1 \\ 0}}^{T} \psi(d_t - g_t) \right\} \tag{1}$$

$$\text{Subject: } g_t = k.h_t.q_t \tag{2}$$

$$h_t = \phi\left(x_t^{avg}\right) - \theta(u_t) - \xi \tag{3}$$

$$x_t^{avg} = (x_{t-1} + x_t)/2 \tag{4}$$

$$u_t = q_t + s_t \tag{5}$$

$$x_t = x_{t-1} + (y_t - u_t).\delta_t \tag{6}$$

$$X^{min} \le x_t \le X^{max} \tag{7}$$

$$q_t \le Q^{max} \tag{8}$$

$$u_t, q_t, v_t \ge 0 \tag{9}$$

where E_y, is the expected value with respect to inflows; t, time stage index (months); T, number of time stages in planning period; ψ, thermal generation cost ($); d, load demand (MW); g, hydropower generation (MW); k, constant efficiency factor (MW/{m^3/s m}); h, net water head *(m)*; x, reservoir storage (hm^3); u, release from reservoir (m^3/s); q, discharge through turbines (m^3/s); s, spillage from reservoir (m^3/s); $X^{min,max}$, limits for reservoir storage (hm^3); Q^{max}, maximum discharge (m^3/s); ϕ, forebay elevation function (m); θ, tailrace elevation function (m); ξ, average penstock head loss (m); y, inflow into reservoir (m^3/s); δ, stage duration (s/10^6).

The objective function, α, (1) aims to minimize over a planning horizon T, the expected value of ψ, expressed as a quadratic function, mainly related with the fuel used at the thermal plants. As d is fixed, these costs, are controlled by g, which is a product of k, h, and q. The constant k includes the water density, gravity acceleration and average turbine/generator efficiency. Two different polynomial functions, up to fourth degree, are used to calculate ϕ and θ.

The variables u, q and s are non-negative and defined for every t. The maximum limit was defined only for q since s is not handled as a decision variable during optimization. The water balance, or state transition, Eq. (6) determines x_t using the previous (or initial) reservoir storage, $x_{(t-1)}$, y, (inflow) and u, (outflow). The conversion constant δ only converts cubic meter per second in cubic hectometer per month. Terms such as evaporation and other water uses have not been considered for the sake of simplicity.

2.1. Markovian stochastic dynamic programming

MSDP determines rules for decision making at each stage of the planning period which will provide the optimal decision for each possible state of the system. Mathematically, the MSDP technique determines a sequence of decision functions, $q^*{}_t(x_{t-1}, y_{t-1})$, mapping the possible states (reservoir storage, past inflow), onto decisions (discharge) that minimize the expected costs.

The MSDP considered here assumes that the stochastic variable, y_t, depends only on the inflow of the previous stage, y_{t-1}. This means that inflows are represented by a first-order periodic autoregressive model, PAR-1, what makes it possible to describe such uncertainty as a Markov chain process.

For each stage, decisions are ranked based on the minimization of the expected sum of the present cost and the future cost, assuming optimal decision-making for all subsequent stages, according to Bellman's Optimality Principle. Therefore the problem can be solved in a recursive way:

$$\alpha_t(x_{t-1}, y_{t-1}) = \min_q E_y \left\{ \psi(d_t - g_t) + \alpha_{t+1}(x_t, y_t) \right\} \tag{10}$$

As we are interested on the control law of the system on stead state, the backward recursion can be computed, starting from the last stage where terminal cost is assumed null, and must be performed until the convergence of the monthly decision functions. This procedure requires, at least, the discretization of the state variable. The control variable can either be discretized or treated as a continuous variable.

Normal (Gaussian) and Log-normal distribution are the most widely used probability density functions (PDF) for inflows modeling [25]. Let y_m represent the inflow data for every month, m = [1,2,...12], the log-normal conditional density distribution function of the inflows, estimated from historical records, can be expressed as in Eq. (11), where ρ_m represents the correlation between two consecutive months, $\mu_{(m|m-1)}$ the conditional mean (12) and $\sigma_{(m|m-1)}$ the conditional standard deviation (13).

$$f(y_m|y_{m-1}) = \frac{1}{\sqrt{2\pi\sigma^2_{m|m-1}}} e^{-\left(\frac{\hat{y}_t - \mu_{m|m-1}}{\sqrt{2}\sigma_{m|m-1}}\right)^2} \tag{11}$$

$$\mu_{m|m-1} = \mu_m + \rho_m \frac{\sigma_m}{\sigma_{m-1}} \left(\hat{y}_{t-1} - \mu_{m-1}\right) \tag{12}$$

$$\sigma_{m|m-1} = \sigma_m \sqrt{1 - \rho_m^2} \tag{13}$$

Conditional probability of discrete inflow ranges, $y_t \in$ (a,b], represented by their average value, y_t^i, can be calculated as in Eq. (14):

$$P\left(y^i_{t|t-1}\right) = \int_a^b f(y_t|y_{t-1})\,dy \tag{14}$$

Finally, the expected cost can be calculated, according to the conditional probabilities of inflows being in the interval represented by y_t^i from N possible ranges, as expressed below:

$$E_{y_{t|t-1}} \left\{ \psi(d_t - g_t) + \alpha_{t+1}(x_t, y_t) \right\} = \sum_i^N \left\{ \psi(d_t - g_t) + \alpha_{t+1}\left(x_t, y_t^i\right) \right\} P\left(y^i_{t|t-1}\right) \tag{15}$$