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Hydrothermal systems operation planning using a discretization of energy interchange between subsystems

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ABSTRACT

This article presents an alternative approach to solve hydrothermal systems operation planning based on stochastic dynamic programming. Under the presented approach, the hydroelectric power plants are grouped into equivalent subsystems of energy and the expected cost functions are modeled by a piecewise linear approximation, by means of the Convex Hull algorithm. Also, under this methodology, the problem is solved independently for each subsystem such that the state variables to be considered are the energy storage and energy net interchange of the subsystem. The presented results have shown that this subsystems separation technique reduces significantly the computation time when compared with the traditional techniques of stochastic dynamic programming, demonstrating the effectiveness of the proposed methodology.

1. Introduction

The main objective of the hydrothermal system operation planning is to determine hydro and thermal generation amounts that minimize the expected operating cost of the system over the considered period. The operational cost comprises fuel costs of the thermal units, energy purchases from neighboring systems and the cost of deficit, which is a penalty for unmet demand [1–3].

The minimization of operation cost on hydrothermal systems basically involves the management of water resources over time by using the capacity of the reservoirs in an optimal manner.

However, the amount of water inflows available in the hydro units at future scenarios is not precisely known. So, the main challenge of long-term hydrothermal operation planning is to determine the opportunity cost of using the water storage.

Among the optimization techniques used in the hydrothermal system operation planning, the technique based on dynamic programming (DP) [3–5] is the most commonly. DP is a sequential process of decision-making that follows the "principle of optimality of Bellman" [6], allowing the recursive solution of the problem. The decision to maintain a reservoir at a given level may have been right depending on the operation strategy and the sequence of inflows to reach the reservoir in subsequent periods. Therefore, the determination of the energy operation planning is characterized by sequential decision-making in which the optimality of a current decision depends on a number of future events. Due to these characteristics identified in the planning, the DP has wide application in solving this kind of problem, because it is appropriate to treat multistage problems and problems with stochastic behaviors through stochastic dynamic programming (SDP).

The techniques based on DP have been proposed over the past years for the solution of the planning problems. In the technical literature can be found several works related to the implementation of DP in the optimal reservoir management.

Yeh [7] presented several techniques that apply reservoir management and operations models, including DP techniques.

In the same way, Labadie [8] presented a review of the state-of-the-art in optimization of reservoir management. In this article, it is evident the importance of using DP in the resolution of reservoir management problem. For example, state increment dynamic

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programing (SIDP) [9], which is a method that utilizes an initial feasible solution and from this an iterative process is used to obtain an improved result using conventional PD. Sampling stochastic dynamic programming (SSDP), a technique that captures the complex temporal and spatial structure of the streamflow process by using a large number of sample streamflow sequences [10–12].

Other techniques to tackle the DP problem include the DP successive approximation (DPSA) method [13], where each reservoir is optimized at a time, assuming a fixed operation for the remaining reservoirs. The two-stage algorithm minimizes total costs from the first-stage decisions plus the total expected future cost, being the cost of all future decisions, which depends on the first-stage solution [14,15]. Incremental dynamic programing and differential dynamic programming [8] were also used in the reservoir optimization problem. These methods are generally useful techniques for the deterministic case; however, they were not successful in the stochastic multireservoir case, as presented by [8].

The use of a SDP was proposed by [16]; this technique allows to incorporate the stochastic behavior of inflows in the planning problem.

The SDP has the disadvantage of requiring the discretization of the state space, which leads to an exponential increase in computational effort, resulting in a phenomenon known as the "curse of dimensionality" [17–19].

Several alternative methodologies have been proposed to solve the problem of combinatorial explosion imposed by SDP, so that it has reasonable computational effort. The most adopted simplification consists in the aggregation of the hydroelectric system in an equivalent energy system, where the hydraulic variables are transformed in energy variables [17,18]. However, according to the number of discretizations, the evaluation of a high number of states may be required, and hence the problem still can become computationally complex.

Another strategy to solve the problem of dimensionality is to use the stochastic dual dynamic programming (SDDP) [3,4,19]. The SDDP uses the technique of Bender's decomposition [20] and treats the problem analytically, and thus it is not necessary to discretize the state space of the system, and this solves the problem of dimensionality. However, the SDDP technique requires a convergence process by running many forward and backward sequences.

Nowadays, the SDDP methodology is used in many countries, as in the case of the Brazilian power system, where the SDDP with aggregated reservoirs is still the official methodology used for determining the long-term hydrothermal system operation.

The use of SDP and SDDP can be observed in Nordic power system. For example, Johannesen and Flatabo [21] presented an overview of the strategy of analysis and methods of solution applied at the Norwegian Research Institute of Electricity Supply for the optimal scheduling of a hydro-dominated power production system. Fosso et al. [22] presented a case study of the deregulated electricity supply system in Norway, and above methods are used. Gjelsvik et al. [23] discuss how SDDP has been applied to hydropower scheduling in the Nordic countries. This work emphasizes the importance of using this method in determining the price of energy in systems with high percentage of hydro generation.

In addition to the aforementioned, several studies have focused on the importance of incorporating network constrains in long- and medium-term hydrothermal operation planning [19,24,25].

Recently, there have been many advances in integrating the DP with other algorithms, mostly including heuristic techniques, such as neurodynamic programming [26,27]; genetic dynamic programming [28] and swarm optimization dynamic programming [29], with just a few applied to the hydrothermal system operation planning. For example, the genetic algorithm was applied to the Brazilian hydrothermal system by Leite [30], producing significant results. Additionally, neural networks were used to model the cost-to-go functions with an efficient state space discretization scheme by Cervellera et al. [31], but using nonlinear optimization. The drawbacks of heuristic and nonlinear methodologies are that they require specialized system knowledge otherwise the optimization solution does not converge to an optimal solution [8].

Finally, there is the alternative of using Convex Hull algorithms [32,33] to obtain the expected cost-to-go functions (ECF) [34,35]. In this case, it uses a smaller number of discretizations by representing these functions with an efficient approach.

Besides these techniques to solve the DP problems, several parallel processing techniques have been used to reduce the computational time in hydrothermal system operation planning [35,36].

The aim of this work is to enable the use of SDP to solve the problems of large hydrothermal system planning, using an alternative strategy in order to reduce the dimensionality of the problem and thus, to reduce the computational time. In this approach, the hydroelectric power plants are grouped into equivalent subsystems of energy and the ECF's are modeled by a piecewise linear approximation, by means of the Convex Hull algorithm.

In this methodology, the subsystems are considered apart to each other, and thus, the variables that make up the state space to determine the ECF's are the initial stored energy and the energy net interchange of subsystem. With this, there are a smaller number of linear programming problems (LPP) to be solved and yet these problems become less complex as a result of the state variables to be discretized. In other words, we are going to solve one problem for each equivalent energy system instead of solving the problem considering all system together. This strategy allows the use of less state variables in each problem (initial storage energy and energy interchange). A preliminary study on the methodology can be observed in Ref. [37].

In this article, the applicability of the proposed methodology is demonstrated through the use of an example system with tutorial purposes. Then, the methodology is used in a reduced equivalent system, based on the interconnected Brazilian power system. The results showed the effectiveness of the proposed methodology when compared with the traditional techniques of SDP and SDDP.

The outline of this article is structured as follows. Section 2 presents a list with the notations and symbols that are used in this article. Section 3 presents a dynamic programming model applied to the long-term operation planning problem and explains how the Convex Hull algorithm is used in the cost-to-go functions formation. Section 4 introduces the proposed methodology. Section 5 illustrates a case study. Finally conclusions are drawn in section 6.

2. Notations and symbols

$\alpha_{t+1}(xt+1)$	Expected operation cost of period $t+1$ associated with state $Xt+1$.
$\mathrm{CDEF}_{i,t}$	Penalty associated to the energy deficit in i-th subsystem and stage t.
$\mathrm{COEFA}_{ci,t}$	Coefficient of c-th cut, concerning the variable final energy stored in i-th subsystem and stage t to composition of ECF.
$\mathrm{COEFB}_{ci,t}$	Coefficient of c-th cut, concerning the variable energy interchanges net in i-th subsystem and stage t to composition of ECF.
$\mathrm{COEFC}_{ci,t}$	Coefficient of c-th cut, for the independent term in i-th subsystem and stage t to composition of ECF.
$\mathrm{CSP}_{i,t}$	Penalty for spillage in i-th subsystem and stage t.
$C_t(U_t)$	Generation cost in the stage t, associated with operative decision U_t
$\mathrm{CT}_{i,t}$	Operation cost of the thermal plant in i-th subsystem and stage t.
$\mathrm{def}_{i,t}$	Energy deficit in i-th subsystem and stage t.
$D_{i,t}$	Total demand in i-th subsystem and stage t.
$\mathrm{ei}_{i,t}$	Energy inflows in i-th subsystem and stage t.
$\mathrm{es}_{i,t}$	Energy stored in i-th subsystem in the beginning of stage t.
$\mathrm{es}_{i,t+1}$	Energy stored in i-th subsystem at the end of stage t.