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The generation of synthetic inflows via bootstrap to increase the energy efficiency of long-term hydrothermal dispatches

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ABSTRACT

One of the most important techniques used to study long-term energy operation planning is the stochastic dual dynamic programme (SDDP). In large systems, hydraulic power plants are aggregated in so-called equivalent energy systems, where the inflows into hydro reservoirs are represented by the affluent natural energy (ANE) and the stored volumes are represented by the stored energy. The stochasticity of energy inflows is captured by the historical series ANE. Currently, ANEs are studied using the Box–Jenkins methodology to fit periodic autoregressive models (PAR(p)) and their order (p). A three-parameter log-normal distribution is applied to the residuals generated via PAR(p) modelling to generate synthetic hydrological series similar to the original historical series. However, the log-normal transformation incorporates non-linearities that affect the convergence in SDDP. This study incorporates the bootstrap statistical technique to determine the order p of the PAR(p) model to generate synthetic scenarios that will serve as a basis for SDDP application. The results indicate the adherence of the proposed method on the operational planning of hydrothermal systems. The proposed methodology in this article could successfully be applied in hydro-dominated systems such as Brazilian, Canadian and Nordic systems.

1. Introduction

The generation of a synthetic series or scenarios of affluent inflows is essential for representing the stochasticity of the affluent inflows with respect to the operational planning process of hydrothermal systems. This can be observed in the hydro-dominated systems, like Brazilian, Canadian and Nordic systems. As an example, the official model in the Brazilian electrical system (BES) is based on a formulation that is based on equivalent energy systems, the affluent inflows to the hydroelectric plants are transformed into affluent natural energies (ANEs). Thus, synthetic series of ANEs are generated instead of synthetic inflow series for each hydro plant [1]. In the computational model officially used in Brazil, the synthetic series are generated through a periodic autoregressive model of order p, PAR(p), which must be adjusted each month due to the periodic characteristics of the inflows. Moreover, if there are changes in the power generation configuration (such as additions of hydropower plants), then the series of energy inflows must comply with the new capacity and the corresponding PAR(p) model must be adjusted for this new situation.

Once the order and the coefficients of the PAR(p) model are estimated, the synthetic series can be built using a residues matrix. However, the structure of the PAR(p) model may allow for the presence of negative values, which are impossible in practice. In other words, a negative value in the synthetic series invalidates the solution of the optimization problem. To solve this problem, the official model adopts a log-normal transformation to ensure that all the values of the synthetic series of ANE are positive.

However, the lognormal transformation introduces non-linearities [2] that can negatively impact the process of convergence of the SDDP optimization model. The main objective of this study is to address this convergence problem. To overcome the instability of the optimization model due to these non-linearities, the log-normal transformation is not used in this study; instead, the random portion is sampled directly from the residues matrix using the Bootstrap technique. This strategy tends to improve the convergence of the optimization model [2] because it avoids the occurrence of

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non-linearity's in the optimization process. The overall formulation of optimization model and the convergence aspects are presented in [3]. Ref. [4] is other article about stochastic dual dynamic programming (SDDP), but it is applied to hydropower scheduling in the Nordic countries.

Considering the previously described situation, the objective of this study is to verify the efficacy of the bootstrap methodology in the determination of the order of PAR(p) models and in the generation of the synthetic scenarios of the ANE series. In addition, these synthetic scenarios were used during the optimization process, which was performed using stochastic dual dynamic programming (SDDP) [3], and its impact on the results was analyzed. Towards this objective, the results obtained by the methodology that is officially used in the national interconnected system (NIS) were faced with the alternative bootstrap method proposed in this article. The conclusion demonstrates that the bootstrap method is an effective methodology for the determination of the model order and scenario generation and permits the acquisition of coherent information regarding the long-term operational planning process for hydrothermal systems.

The bootstrap technique has not yet achieved broad application in energy time series. Some studies that have adopted the method are highlighted below.

The importance of the bootstrap technique was accentuated in the study of the time series for the prediction of energy demand in the American market in 1984 [5]. In 1986, Chatterjee [6] estimated the standard error of estimations of the parameters of the prediction models. In 1991, Neto compared the behaviours of the bootstrap and the Box and Jenkins classical methodology in the identification of the structure of the AR(1), AR(2), MA(1), MA(2), and ARMA(1,1) models [29].

In a time series, the bootstrap method can be applied to the residuals or as moving blocks [6,7]. To apply the bootstrap method to the residuals, one must consider that the data have a time relationship and can form probabilistic models in which the residuals are independent. The generated residuals are randomly and independently selected B times with replacement, generating B bootstrap samples. Next, the series are assembled using the adjusted model and the randomly selected residuals. In the moving blocks method, proposed in [32], from an original sample ($Z_1, Z_2, Z_3, \ldots, Z_n$), k blocks of size "M" are randomly selected, with replacement, to form the bootstrap samples. The process is repeated B times, generating the new series. This method requires the second-order stationarity of the original series and the difficulty of defining the best size of block M.

The bootstrap method was used as an alternative procedure for determining the order of the autoregressive model applied to the series of ANEs, see [2].

The operational planning problem of hydrothermal systems considering different planning time frames was presented in [9]. Carneiro [10] analyzed the resolution techniques for long- and medium-term planning, describing their primary characteristics, advantages and disadvantages.

Different algorithms based on the use of network inflow for resolving the hydrothermal energy planning problem are presented in [11–16].

Christoforidis et al. [17] proposed a methodology for the operational planning of systems that involve predominantly hydraulic forms of generation, making use of the techniques of load prediction and maintenance scheduling through the primal-dual interior point method.

A model that integrates the operational planning and system reliability by considering the stochasticity of energy demand and the affluent inflows from reservoirs was presented by Amjady et al. [18].

The use of a hybrid representation for the reservoirs of the hydroelectric plants (equivalent and individualized reservoirs) was proposed by Marcato [19]; this representation allowed further studies to be conducted, such as the economic and operational viability of hydroelectric plants, system representations with strong operational restrictions, and flood control studies, among others.

Labadie [20] presented several techniques that apply stochastic optimization to the operational planning of hydrothermal systems, such as linear programming, linear stochastic programming, non-linear programming, network inflow, discrete dynamic programming, stochastic dynamic programming, differential dynamic programming, discrete-time optimal control theory and stochastic optimal control. Nandalal and Bogardi [21] presented optimization techniques based on incremental dynamic programming and stochastic dynamic programming for optimal reservoir operation; they also presented decomposition and aggregation/disaggregation methods as well as methods based on equivalent reservoirs.

A new proposal for modelling future cost functions in medium-term operational planning for use in stochastic dynamic programming (SDP) was presented by [22] and [28]. In this proposal, the convex hull algorithm was used to obtain a series of hyperplanes that constitutes a convex set through the discretization of the state space.

Artificial intelligence techniques were applied to resolve the operational planning problem for hydrothermal systems. For example, [23] involved a comparative study of non-linear programming based on the network inflow of the "HydroMax" programme [24] against evolutionary computation (genetic algorithm). Monte and Soares [25] applied an adaptive neural-fuzzy inference system, and the methodology worked in parallel with a deterministic optimization model that considered inflow rate prediction; in addition, Antunes [26] applied an artificial intelligence technique based on the behaviour of ant colonies, where the results indicated similar behaviour to that obtained by non-linear programming techniques. Further, Rodrigues et al. [27] proposed the use of neural-dynamic programming (NDP), that is, the behaviour was observed through simulations and, with this, the actions were improved through reinforcement using iterative techniques that sought to improve the capacity to estimate the future cost function.

The remainder of the paper is organized as follows: Section 2 presents the bootstrap methodology and its application to determine the order of the models and the generation of the scenarios. Section 3 presents information that is essential for analysing the work presented in the case study section. Section 4 describes the results of the proposed method, and Section 5 presents the main conclusions.

2. Bootstrap method

The bootstrap method was first proposed in [32], where $x = (x_1, x_2, \ldots, x_n)$ corresponds to the initial sample with "n" elements of a population, which has an unknown probabilistic model and that follows an "F" cumulative distribution function. Therefore, "B" bootstrap samples of size "n" are formed from the initial sample, which is represented by Eq. (1), and are obtained by random sampling with replacement.

$$\begin{aligned} x^{*1} &= (x_1^{*1}, x_2^{*1}, \ldots, x_n^{*1}) \\ x^{*2} &= (x_1^{*2}, x_2^{*2}, \ldots, x_n^{*2}) \\ x^{*B} &= (x_1^{*B}, x_2^{*B}, \ldots, x_n^{*B}) \end{aligned} \tag{1}$$

The non-parametric modelling of the bootstrap technique allows for important information to be extracted without specific knowledge of the population from which the sample was extracted;