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A time series model for building scenarios trees applied to stochastic optimisation

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ABSTRACT

Given the dependence on hydrologic regimes, the uncertainty in energy planning in Brazil requires adequate and coherent stochastic modelling. The structure used to simulate synthetic series in the current Brazilian Electrical Sector model generates nonlinearity in the model equation via lognormal distribution adopted for the model residuals. This nonlinearity can cause non-convexity problems in calculating the Cost to Go Functions, which are formed by convex polyhedral approximation through piecewise linear functions. Given the above considerations, the stochastic model characteristics used to generate a scenarios tree and its use in optimisation models, this study proposes the development of an alternative methodology for scenario construction. Thus, a new general approach is proposed for constructing trees used in the stochastic optimisation processes. This simulation structure combines the computationally intensive Bootstrap technique and Monte Carlo simulation method. Scenario trees were generated using a time horizon consistent with the long-term hydrothermal dispatch planning. The synthetic series were compared to the historical series through statistical tests, which demonstrated that the developed model was sustainable during the stochastic portion of the experiment. Finally, the tree paths were applied to the Stochastic Dual Dynamic Programming, and various response variables were analysed. Such analysis support the conclusion that the model herein can reproduce structures that are compatible with the current model without nonlinearity in the stochastic model equation and non-convexity in the Cost to Go Functions.

Introduction

The size and characteristics of the Brazilian electrical energy production and transmission system are unique. The system includes a large-scale hydrothermal power system with many hydroelectric plants and multiple owners. The National Interconnected System (NIS) is composed of companies (generation, transmission, distribution and commercialization) from the South, Southeast/Midwest, Northeast and North regions.

An important characteristic of predominantly hydroelectric power generation systems is a strong dependence on hydrologic regimes. Thus, planning energy operations includes determining power generation goals for the hydroelectric and thermoelectric power plants at each stage in the study horizon and meeting the electrical energy demand, power plant operational restrictions and electrical restrictions [30].

Due to the dependence on hydrologic regimes, the uncertainty associated with energy planning in Brazil requires appropriate and coherent stochastic modelling for the hydrologic series. The hydrologic scenario tree generation models are important and necessary for optimising the system operation performance due to the consequent increases in benefits and reliability, as well as cost reduction.

The NEWAVE model is officially employed for long-term energy operation planning [6]; this model determines optimal water and thermal resource allocation for each month during the planning period, which can vary from 5 to 10 years, by minimising the expected operating cost. The hydroelectric power facility is represented as an aggregate, and the operational policy calculations are based on Stochastic Dual Dynamic Programming (SDDP).

The NEWAVE model considers various scenarios for affluent energies, generated through stochastic simulations using periodic autoregressive structures, PAR(p), [37]. In the NEWAVE model, the problem is formulated based on equivalent energy systems [2], by considering on the four subsystems that compose the NIS.

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In this formulation, the hydrologic series are transformed into affluent natural energy (ANE).

ANE stochastic modelling is performed using the PAR(p), which fits an autoregressive model of order p to each historical series stage that composes the system configuration. It is important to mention that the main model's objective is the scenarios simulation, not forecasting. An overview of the main methodologies used in electricity price forecasting is available in [1]. In the scenario simulations, the current NEWAVE version employs a lognormal transformation to generate the synthetic series, which produces non-convexity in the SDDP model, according to [6]. Lognormal distribution is used to simulate hydrologic scenarios because it generates non-negative values for the stochastic variables.

Recent publications present alternatives to the current model for long-term operation planning. In [36], the authors propose a new approach that uses the Bootstrap [13] and SDP-convex hull techniques [12].

The objective of this study is to propose a new methodological approach to generate synthetic scenario tree series in stochastic optimisation models. In particular, the proposed method can be applied to long-term energy operation planning in Brazil through SDDP. In this context, the literature includes simulation mechanisms for stochastic variables that produce a non-linear structure in the generating model, which produces undesirable non-convexity in constructing an objective function for the stochastic optimisation process. In this study, the scenario tree is constructed using the non-parametric Bootstrap technique and the Monte Carlo simulation method, which differ from the current forward and backward recursions.

The remaining of the paper is organised as follows: Sections 'Stochastic Dynamic Programming applied to hydrothermal power system operation planning' and 'Scenarios tree modelling' are dedicated to bibliographical reviews; Section 'Stochastic Dynamic Programming applied to hydrothermal power system operation planning' is related to the dynamic optimisation approaches; and Section 'Scenarios tree modelling' discusses stochastic scenario tree generation. Section 'Results' describes some results obtained with the proposed method, while Section 'Conclusions' presents the main conclusions.

Stochastic Dynamic Programming applied to hydrothermal power system operation planning

To optimise hydrothermal power systems, multiple techniques that use linear, nonlinear and dynamic programming are available in the literature. In [24], mixed integer programming and nonlinear network flow algorithms are employed to optimise cascade reservoirs. Dynamic programming is also broadly considered in the literature, such as in [40]. In [36], a Stochastic Dynamic Programming methodology was proposed based on the convex hull. In [22], a new optimisation strategy based on Adaptive Modified Firefly Algorithm is used to investigate the effect of uncertainty on the optimal operation management of Micro Grids.

In Brazil, SDDP is used for the model in chain energy operation planning [31]. This methodology generates linear approximations for the Cost to Go Function (CGF) using Benders' decomposition technique [4], and it models inflow uncertainty through a periodic autoregressive model in which past inflows are the state variables. Benders' decomposition divides the problem into various stages; each stage depends on the subsequent stage through interactive forward and backward steps.

The forward step includes the process initiated at the second stage and finalised in the last stage. This process involves direct recursion but not including information related to future operating costs in the first iteration. In this case, optimisation problems at each stage are solved through linear programming techniques [9]. This way, the model tends to use, at each stage, the maximum capacity of the hydro plants, which enhances thermoelectric power plant use in the future and a possible deficit.

The backward recursion follows the opposite path: it begins at the last stage and ends at the second stage. At each new stage it is generated a constraint related to the previous one, which brings important information related to the estimation of the CGF.

For hydrothermal power system operation planning, the stochasticity is introduced via simulating the realization of the stochastic variables at various planning horizons, which characterise the multiple stages.

The first step in the process is to determine the number of realizations that comprise the backward simulations, i.e., is the number of drawings related to the inflow scenarios generated at each planning stage. These realizations will be considered in the recursive simulation, in the estimation of the Bender's cuts and in the definition of the forward paths. For example, if we choose 20 branches and 60 monthly planning periods (5 years), a matrix of dimension 20×60 is obtained. As such, in the forward procedure it would be possible to form 20^{60} possible paths. In the current model, the branches are selected once at the beginning of the process for all stages. The objective of this work is to reformulate this premise and allows more flexibility in the realizations choice.

The second procedure is the determination of the number and order of transitions among the sequences that will be travelled during the forward optimisation process. It is just these definitions that determine the paths that will be visited in the scenarios tree, to be discussed in Section 'Scenarios tree modelling'. As stated in [30], a sample of 200 paths (out of the 20^{60} possibilities) is recommended, as this choice is enough to guarantee the convergence of the optimisation algorithm.

Once such values are established, the optimisation system is formulated as follows.

Let i be the number of equivalent subsystems and T be the number of stages in the planning horizon. The objective function for the problem is as follows:

$$Y_t = \min \sum_{k \in NS} \sum_{j \in NUT_k} CT_j GT_{i,j} + \frac{1}{1+\beta}\alpha_{t+1} \tag{1}$$

This function has the following constraints:

(i) *Water balance constraint:*

$$\begin{aligned} &EA_{t+1}^k = EA_t^k + FC_t^k EC_t^k - GH_t^k - EVT_t^k - EVM_t^k - \\ &EVP_t^k - EM_t^k - EDVC_t^k \\ &k = 1, \ldots, NS \end{aligned} \tag{2}$$

(ii) *Demand constraint:*

$$\begin{aligned} &GH_t^k + \sum_{j \in NUT_k} GT_{t,j} + \sum_{j \in \Omega_k} (F_{t,i,k} - F_{t,k,i}) + DEF_{t,k} - EXC_t^k = \\ &D_t^k - EVM_t^k - EFIO_t^k - \sum_{j \in NUT_k} GTMIN_{t,j} - EDVF_t^k \\ &k = 1, \ldots, NS \end{aligned} \tag{3}$$

(iii) *Thermal power generation limits constraint:*

$$\begin{aligned} &0 \leqslant GT_{t,j} \leqslant \overline{GT}_{t,j} \\ &\forall j \in NTP_k \\ &k = 1, \ldots, NS \end{aligned} \tag{4}$$

(iv) *Exchange capacity limits constraint:*

$$\begin{aligned} &|F_{t,i,k}| \leqslant \overline{F}_{t,i,k} \\ &i = 1, \ldots, NS \\ &k = 1, \ldots, NS \end{aligned} \tag{5}$$