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SHORT-TERM RESERVOIR OPTIMIZATION BY STOCHASTIC OPTIMIZATION TO MITIGATE DOWNSTREAM FLOOD RISKS

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An important objective of the operation of multi-purpose reservoirs is the mitigation of flood risks in downstream river reaches. Under the assumptions of reservoirs with finite storage volumes, a key factor for its effective use during flood events is the proper timing of detention measures under consideration of forecast uncertainty. Operational flow forecasting systems support this task by providing deterministic or probabilistic inflow forecasts and decision support components to assess optimum release strategies. We focus on the decision support component and propose a deterministic optimization and its extension to an adaptive multi-stage stochastic optimization. These techniques are used to compute release trajectories of the reservoirs over a finite forecast horizon of up to 15 days by integrating a nonlinear gradient-based optimization algorithm and a simulation model of the water system.

The framework has been implemented for a reservoir system operated by the Brazilian Companhia Energética de Minas Gerais S.A. (CEMIG). We exemplary present results obtained for the operation of the Tres Marias reservoir in the Brazilian state of Minas Gerais with a catchment area of near 55,000 km^2. The focus of our discussion is the impact of forecast uncertainty and its consideration in the optimization procedure. We compare the performance of the deterministic and multi-stage stochastic optimization techniques and show the superiority of the stochastic approach.

INTRODUCTION

We conduct this research in the scope of the HyProM project (Short-Term Hydropower Production and Marketing Optimization) sponsored by the Bonneville Power Administration

(BPA), Companhia Energtica de Minas Gerais S.A. (CEMIG), Deltares and Fraunhofer IOSB-AST. The project team includes staff of the sponsors, the Brazilian research institute LACTEC, and researchers from the academic sector. Main focus is the short-term management of hydropower reservoir systems under the explicit consideration of forecast uncertainty as well as the integrated management of hydropower production and marketing. The project started in December 2012 and will continue till April 2015. In this paper, we present results obtained for the Brazilian reservoir system of CEMIG. A focus of this work is the flood management of the reservoirs aiming at mitigating downstream food risks.

In water systems operation, optimal centralized control can be achieved by employing Model Predictive Control (MPC) (Ackermann et al. [1], van Overloop [12]). Key elements of MPC are (Morari et al. [11]): (1) a model of the physical process to predict future trajectories of the controlled variables over a finite horizon, (2) the calculation of a control sequence that optimizes an objective function, and (3) a receding horizon strategy. The receding horizon strategy means that, at each forecast time and control instant $T0$, the first signal of the control sequence is applied and the horizon is shifted ahead. Constraints on inputs, states and outputs are explicitly considered (Schwanenberg et al. [15]).

Contrary to conventional reservoir operation strategies, where operating rules are calculated offline, MPC considers the online solution of an optimization problem at every time step. Available disturbance forecasts, i.e. reservoir inflows and laterals in downstream river reaches, can be used directly in the control scheme, resulting in advantages and threats. The main advantage is that the control strategy becomes proactive (Zavala et al. [17]). Before the realization of a forecasted disturbance, the control sequences set the system to a state optimal to accommodate it, for example by lowering the water elevation in a reservoir before an expected flood event occurs. However, use of forecasts can also jeopardize the control robustness (Bemporad and Morari [2]), if MPC is applied in a deterministic mode and forecast uncertainty is high. The approach runs the risk of suggesting decisions in anticipation of expected events that eventually do not occur. To increase the robustness of MPC, enhancements of the approach extend the deterministic optimization to a multi-stage stochastic optimization (Raso et al. [14]).

METHOD

Model Predictive Control (MPC) considers a discrete time-dynamic system according to

$$\begin{aligned} x^k &= f(x^{k-1}, x^k, u^k, d^k) \\ y^k &= g(x^k, u^k, d^k) \end{aligned} \tag{1}$$

where x, y, u, d are respectively the state, dependent variable, control and disturbance vectors, and $f(\,)$, $g(\,)$ are functions representing an arbitrary linear or nonlinear water resources model. If being applied in MPC, Eq. (1) is used for predicting future trajectories of the state x and dependent variable y over a finite time horizon represented by $k = 1,\ldots,n$ time instants, to determine the optimal set of control variables u by an optimization algorithm. Under the hypothesis of knowing the realization of the disturbance d over the time-horizon, for example the inflows into the reservoir system, a so-called multiple-shooting version (Diehl [7]) of the nonlinear MPC becomes

$$\min_{u,x^*\in\{0..T\}} \sum_{k=1}^{n} J(x^k, y^k, u^k) + E(x^N, y^N, u^N) \tag{2}$$

$$\text{subject to:} \quad h(x^{*,k}, y^k, u^k, d^k) \le 0, \qquad k = 1, ..., N \tag{3}$$

$$x^{*,k} - f(x^{*,k-1}, x^{*,k}, u^k, d^k) = 0 \tag{4}$$

where $J(\ )$ is a cost function associated with each state transition, $E(\ )$ is an additional cost function related to the final state condition, and $h(\ )$ are hard constraints on control variables and states, respectively. The notation x^* refers to a subset of state variables which become independent optimization variables. In this case, the related process model becomes an equality constraint of the optimization problem (Eq. 4) such as in a simultaneous or collocated optimization setup. The remaining state variables as well as the dependent variables y get computed by a simulation model according to Eq. (1) corresponding to a sequential or single-shooting optimization setup. Xu & Schwanenberg [16] compare pros and cons of the two methods from the perspective of control efficiency, constraints handling and scaling.

The extension of the deterministic to a stochastic optimization is achieved by replacing the single-trace forecast by a forecast ensemble and computing the objective function values J and E as the probability-weighted sum of the objective function terms of the individual ensemble branches or scenarios. This lead to a formulation according to

$$\min_{u,x^*\in\{0..T\}} \sum_{j=1}^{m} \sum_{k=1}^{n} p_j [J_j(x^{j,k}, y^{j,k}, u^{\mathbf{M}(j,k)}) + E_j(x^{j,N}, y^{j,N}, u^{\mathbf{M}(j,N)})] \tag{5}$$

where p_j is the probability of the scenario $j = 1,\ldots,m$ and m is the total number of scenarios. Whereas the disturbance d as well as the model states x and outputs y are treated independently in each scenario, the control variable u is the key to the properties of the stochastic optimization approach. The most general formulation is achieved by the use of scenario trees. One way for its definition is the scenario tree nodal partition matrix $\mathbf{M}$ (j,k) (Dupacova et al. [8]) with the dimensions m × n. The matrix assigns the control at time step k of scenario j to the control vector u. This enables us to define a common control trajectory for all scenarios at the beginning of the forecast horizon when future system states are still uncertain. When uncertainty gets resolved over the forecast horizon, for example when a forecasted precipitation is finally observed, we introduce branching points and receive an independent control in each scenario at the end of the forecast horizon. Eq. 6 presents an example of a nodal partition matrix for a simple tree with two scenarios and a branching point at the second time step.

$$\mathbf{M} = \begin{bmatrix} 1 & 2 & 3 & 4 \\ 1 & 2 & 5 & 6 \end{bmatrix} \tag{6}$$

The introduction of multiple branching points at several time steps leads to a multi-stage stochastic optimization; check Raso et al. [14] for details.

From a technical perspective, the solution of the multi-stage stochastic optimization (Eq. 5) is very similar to the solution of the deterministic setup of Eq. (2). The main difference is the number of dimensions of the optimization problem. According to our experience, it is typically increasing by a factor of 5-20 if we derive the scenario tree from a meteorological ensemble forecast.

USE CASE: TRES MARIA RESERVOIR

Use Case Description

The Três Marias hydropower reservoir is located in the São Francisco River in the center of Minas Gerais state, Brazil, with a drainage area of approximately 55,000 km² (Figure 1). The region of interest in this use case extends to Pirapora city, located 120 km downstream of the reservoir. The operation of Três Marias reservoir is responsible for flood control and mitigating flood inundation in Pirapora.

The Três Marias dam was built during the 1950's. Its reservoir has a total capacity of 19.5×10^9 m^3, with strategic importance for Brazil. It serves multiple purposes: hydropower generation, flood control, navigation, municipal and industrial water supply and irrigation. For Brazilian standards, Três Marias is a watershed covered by a dense network of meteorological and fluviometric gauges. Many of them include telemetry with real-time data available from the National Water Agency (Agência Nacional de Águas – ANA) and CEMIG.

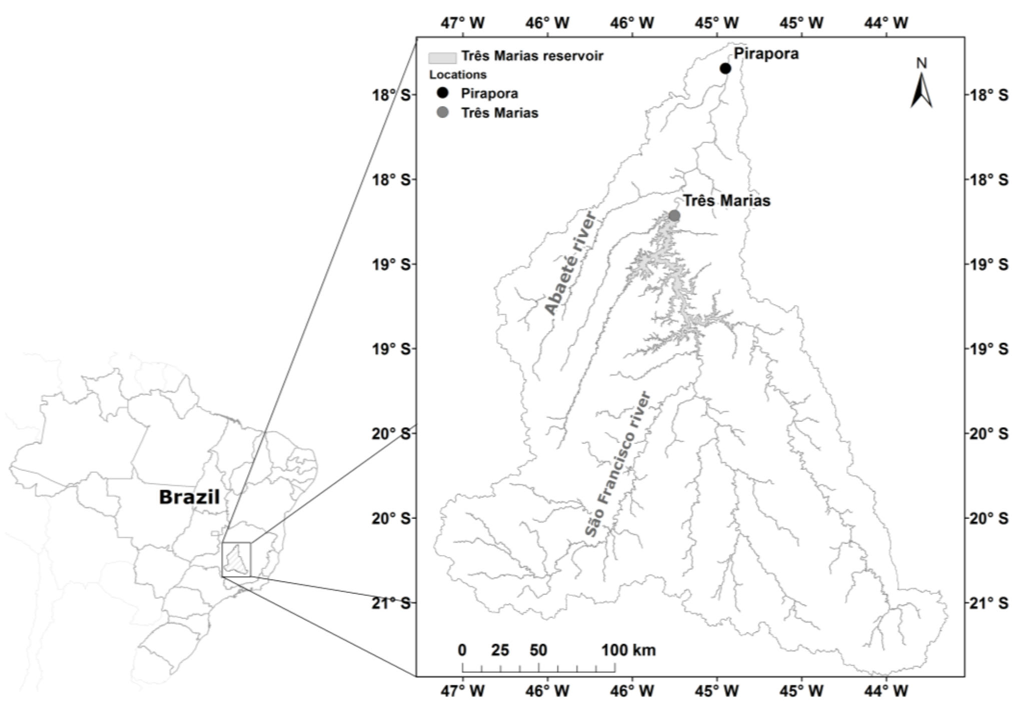


Figure 1. São Francisco river basin (until the confluence with Rio das Velhas upstream of Pirapora city), major rivers of the region and the location of Três Marias reservoir

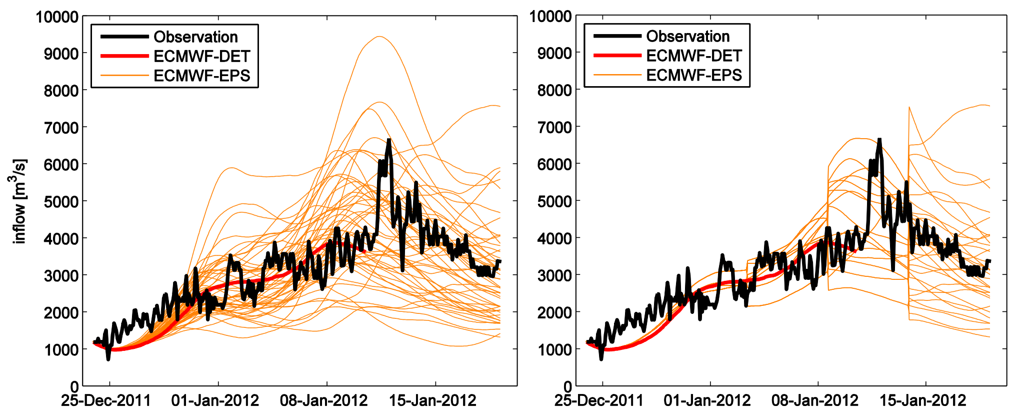
Ensemble Streamflow Predictions and Scenario Tree Generation

In this study, Quantitative Precipitation Forecasts (QPF) from the global Ensemble Prediction System (EPS) provided by the European Centre for Medium-range Weather Forecasts – ECMWF (Molteni et al. [10], Buizza et al. [3]), are used as meteorological forcing of the hydrological forecasting model. The data of this assessment is obtained from "The Observing

System Research and Predictability Experiment" (THORPEX) Interactive Grand Global Ensemble (TIGGE) project portals (Bougeault [5]).

The ECMWF-EPS forecasts consist of 50 members of perturbed precipitation of 0.5 degrees resolution produced for the whole globe considering initial uncertainties by using singular vectors and model uncertainties due to physical parameterizations by a stochastic scheme (Buizza et al. [4]). The data becomes available twice a day at 00:00 UTM and 12:00 UTM with a forecast horizon of 15 days and time steps of 6 hours. For the use in the hydrological model, it is spatially downscaled to the watershed by Thiessen polygons and disaggregated to hourly time steps. As a reference and comparison between deterministic and probabilistic results, we also consider the deterministic forecast provided by ECMWF. It is also available in the TIGGE portal.

We use the MGB-IPH (Modelo de Grandes Bacias – Instituto de Pesquisas Hidráulicas) model (Collischonn et al. [6] Paiva et al. [13]) to conduct streamflow forecasts based on the meteorological forcing. The model is a large-scale distributed hydrological model that calculates streamflow from precipitation data. In application to the São Francisco river basin, the model is calibrated considering hourly time-steps using the rainfall and streamflow data of the gauge network in the period from December 2006 until June 2011. Figure 2a presents an ensemble inflow forecast to the Três Marias reservoir based on the ECMWF ensemble forecast, and the generated scenario tree. The forecast was issued on December 27, 2011, and shows a forecast for one of the major flood events of the last ten years.



a) b)

Figure 2. Example of a) an ensemble inflow prediction issued on December 27, 2011, into the Tres Marias reservoir based on the ECMWF ensemble forecast and b) the related binary scenario tree with 32 branches

The scenario tree in Figure 2b is built with a fixed binary structure of maximum size. First, the number of ensemble members is reduced to the next smaller power of two. Then, branching points of the tree are introduced at equidistant time steps over the forecast horizon. The tree is constructed by reducing the number of the remaining ensemble members at every branching point, starting with the last branching point. The reduction of the ensemble members as well as the tree construction relies on a backward reduction strategy (Gröwe-Kuska et al. [9]).

Deterministic and Multi-Stage Stochastic Optimization

The short-term management of the Três Marias reservoir during flood events implements the following components:

i. Spill is undesired. A linear penalty on spill minimizes the spill volume over the forecast horizon.
ii. If spill is unavoidable, the main motivation results from the compliance with a time-dependent maximum forebay elevation constraint. It represents longer-term objectives during the wet season by allocating flood control storage. It is enforced in the model by a hard constraint.
iii. Two flow thresholds at the gauge Pirapora Ponte exist at 2000 and 3800 m^3/s (larger scale inundation at the city of Pirapora starts at 4000 m^3/s). Both are implemented as soft constraints and penalize an up-crossing in a least square sense. The first one has a much lower weighting coefficient than the second one.
iv. A rate-of-change penalty on the reservoir outflow smooths the solution and avoids high outflow gradients.

Figure 3 presents deterministic and stochastic optimization results for the total outflow, spill and forebay elevation of the reservoir as well as the flow at the gauge Pirapora Ponte for a forecast time of December 27, 2011. Deterministic results base upon perfect forecasts with a forecast lead time of 10 and 15 days. Therein, the streamflow forecast of the hydrological model is replaced by observed data. Another deterministic optimization uses the MGB streamflow forecast forced with the deterministic ECMWF forecast of 10 days. The stochastic optimization relies on the scenario tree of 32 final branches with a lead time of 15 days as presented in Figure 2b.

Deterministic results with a lead time of 10 days show similar results. Since they do not include the peak inflow beyond Day 10, the forebay elevation increases faster and flow at the downstream gauge is lower than in the optimization runs with a lead time of 15 days. The latter detect the peak and foresee an average flow at the downstream gauge larger than the first threshold of 2000 m^3/s. The least-square penalty motivates the optimization to prefer a constant flow at Pirapora Ponte by choosing an appropriate reservoir outflow under consideration of the flow propagation to the gauge and lateral inflows from downstream tributaries.

The stochastic optimization takes into account forecast uncertainty and propagates it through the decision-making process. It shows a more conservative allocation of reservoir storage, i.e. a lower forebay elevation compared to the deterministic optimization. On the other hand, the total reservoir outflow is larger from the beginning. The reason for this is the forebay elevation hard constraint. While the deterministic runs fulfill the constraint only for the most probable scenario (without considering forecast uncertainty), the control trajectory of the stochastic optimization meets the constraint for all 32 branches of the scenario tree. In the operational context, this leads to a much higher chance of meeting the constraint for a range of potential future inflows. An alternative and less conservative approach is the formulation of the forebay elevation bound as a chance constraint. In this case, the optimization accepts a limited probability of a forebay elevation violation.

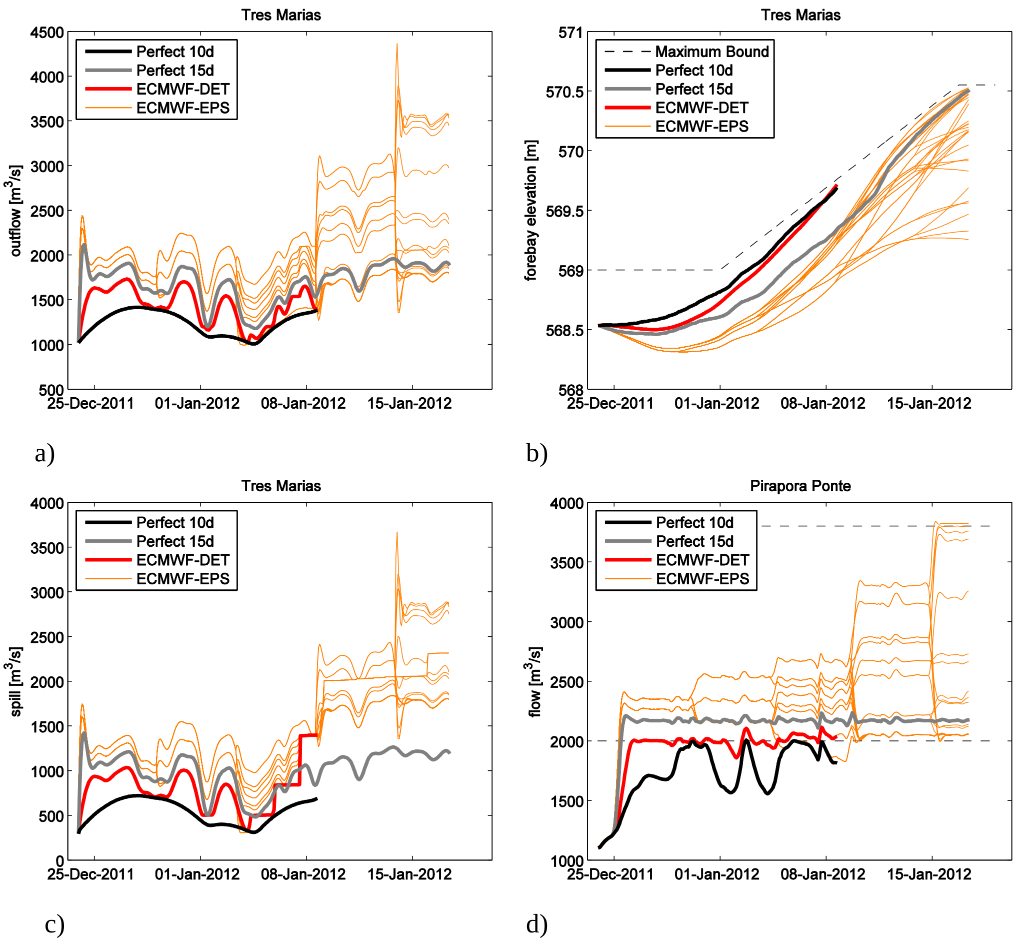


Figure 3. Deterministic and stochastic optimization results for a forecast time of December 27, 2011: a) total reservoir outflow, b) forebay elevation of the reservoir, c) spill, d) flow at the downstream gauge at Pirapora Ponte

CONCLUSIONS

The use of probabilistic forecasts in combination with multi-stage stochastic optimization techniques in comparison to a deterministic approach has a number of advantages in application to short-term reservoir management. One is that probabilistic forecasts are available for longer lead times, in our case 15 days compared to 10 days for the meteorological model of ECMWF. This leads to an earlier detection of critical events and its better anticipation by more in time decisions. Another one is the propagation of forecast uncertainty through the decision-making process and its visualization for the stakeholder. This permits risk-based and more robust decisions.

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