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FLOOD CONTROL RESTRICTIONS FOR A HYDROELECTRIC PLANT

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SYNOPSIS

This paper presents a methodology to impose bounds on the yield of one reservoir in order to keep flood risk below a pre-established level. This is accomplished by an efficient backward recursion scheme which mimics the real time operation of the reservoir. Synthetic traces are used to take the streamflow stochasticity into account.

The performance of the methodology is evaluated through the case study of the Três Marias power plant, which reservoir can be used to protect a city located 150 km downstream. Flood control bounds were calculated for different hypothesis regarding forecasted maximum release, ranging from no information to perfect information.

INTRODUCTION

The operation objectives of a reservoir system primarily designed to meet conservative purposes may change with time. A typical example arose when the operating rules of the brazilian hydroelectric system, originally designed to optimize power production, were reevaluated in order to take flood control constraints into account.

The methodology described in this paper provides daily bounds on the yields of one reservoir as a function of its stored volume. These bounds ensure that the probability of causing downstream damage is kept below a pre-established acceptable level. Downstream damage is said to occur whenever the maximum safe release is violated. This usually happens when the reservoir reaches the maximum volume for normal operation (v_M) and dam-safety procedures override any flood control restriction (Kelman et al., 1980). Another critical situation may take place if a sizeable part of the total flow at the site to be protected comes from tributaries joining the main river downstream to the dam. In this case the daily maximum release is the difference between the actual maximum flow at the site and the uncontrolled flow. In other words, the reservoir maximum yield depends on a random variable whose probability distribution will be estimated according to the forecasting capability. Forecast errors in this real time decision process may lead to "optimistic" maximum releases at the reservoir and cause downstream damage even when the reservoir is not full.

Flood control restrictions may prevent the reservoir from filling up at the end of the rainy season (Costa et al., 1981). A simulation study compares the stored volumes obtained under different hypothesis regarding the forecast model. The difference between these volumes can be used to assess the worth of an improvement on forecasting capability.

OUTLINE OF THE METHODOLOGY

Basic Concepts and Notations

- h – duration of the wet season (days)
- $v(t)$ – stored volume (m^3) at the beginning of day $t, t=1,2,\ldots h$
- v_M – maximum stored volume (m^3) for normal operation. Dam-safety procedures (emergency) occurs whenever $v(t)>v_M$
- $q(t,i)$ – total inflow (m^3/day) at the reservoir during day t for the i-th sequence. A sequence is one time series of daily flow for the rainy season obtained from gauge readings or from synthetic daily streamflow models.
- $d_E(t,v(t))$ – outflow discharge (m^3/day) necessary to meet the energy demand
- $d(t)$ – outflow discharge (m^3/day) during day t. Bounds will be imposed on this variable.
- $d_M(t,i)$ – maximum outflow discharge (m^3/day) at the reservoir which does not cause downstream damage. An emergency occurs whenever $d(t)>d_M(t,i)$.
- z – maximum safe flow (m^3/day) at the site to be protected. Notice that z does not depend on the sequence.
- $y(t+\tau,i)$ – uncontrolled flow (m^3/day) at day $t+\tau$ (τ being the time lag) at the site to be protected for the i-th sequence.

The above definitions lead to

$$d_M(t,i) = z - y(t+\tau,i) \tag{1}$$

As $y(t+\tau,i)$ is not perfectly known, $d_M(t,i)$ will be estimated based on the best available data as

$$\hat{d}_M(t,i) = z - y_\beta(t+\tau,i), \text{where} \tag{2}$$

$y_\beta(t+\tau,i)$ is such that

$$P[Y(t+\tau,i) > y_\beta(t+\tau,i) | I_t] = \beta(t) \tag{3}$$

where $\beta(t)$ is the acceptable forecast failure probability and I_t is the available information at day t.

Establishing Lower Bounds

The evolution of reservoir storage for the time interval $(t+1,h)$ is uniquely determined by the knowledge of the initial volume $v(t+1)$, the inflow sequence i during $(t+1,h)$ and the operating rules for this interval.

Let $v_s(t+1,i)$ be a "safe" initial volume, that is, no simulation with $v(t+1,i) \leq v_s(t+1,i)$ causes any downstream damage during $(t+1,h)$. The critical volume for day t and sequence i is defined as

$$c(t+1,i) = \text{Max}\{v_s(t+1,i)\} \tag{4}$$

↑ over what?
or max between what?

If $c(t+1,i)$ and $q(t,i)$ are known, it is possible to derive a critical operating rule for day t and sequence i. This rule will produce for every $v(t)$ the outflow discharge $d(t,i)$ in day t which results in a stored volume equal to $c(t+1,i)$ in day t+1. The critical operating rule is easily obtained from the continuity equation

$$d(t,i) = v(t) + q(t,i) - c(t+1,i) \tag{5}$$

Since $c(t+1,i)$ and $q(t,i)$ are supposed to be known, equation (5) can be seen as a linear relation between $d(t,i)$ and $v(t)$ of the form

$$d(t,i) = v(t) - b(t,i), \text{ where} \tag{6}$$

$$b(t,i) = c(t+1,i) - q(t,i) \tag{7}$$

Figure 1 shows critical operating rules for a random sample of 10 sequences.

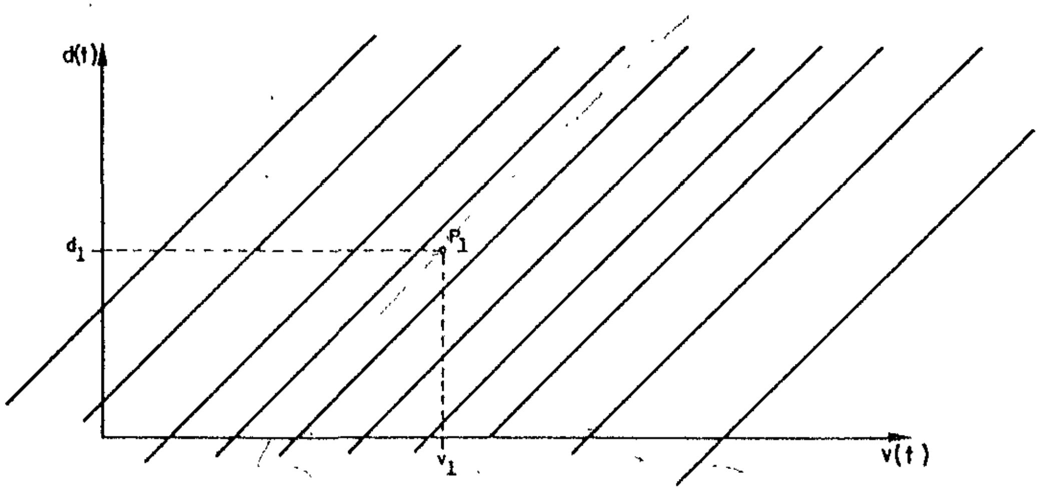

Figure 1. Critical Operating Rules

Suppose point P_1 represents a feasible outflow d_1 for $v(t) = v_1$. One can see that the four critical rules to the left of P_1 require outflows greater than d_1 (for $v(t) = v_1$) in order to avoid emergencies in (t+1,h). Since all sequences are equally likely, decision d_1 will lead to emergencies in four cases out of ten, i.e., the probability of emergency for the point P_1 can be estimated as 40%.

Any point located in the 45^0 line that passes through P_1 (Figure 1) is associated with a risk equal to 40%. All points to the "left" of this line will be associated with lower risks while points to the "right" will lead to higher risks. In other words, this line defines a lower bound on the yield in order to keep the probability of having an emergency in the interval (t+1,h) lower than 40%.

All critical rules are uniquely defined by any of their points, for example, b(t,i). The set {b(t,i),i=1,...} can be seen as one sample of a random variable B(t). If $\alpha(t)$ is the acceptable probability of downstream damage in the interval (t+1,h), then the value $b^*(t)$ associated with this risk will be defined by

$$P\{B(t) \leq b^*(t)\} = \alpha(t) \tag{8}$$

The critical rule associated with $b^*(t)$ constrains the reservoir yield to be at least $v(t) - b^*(t)$.

Calculation of the Critical Volume for Day t

The actual release rule of a reservoir depends on many factors such as the energy load and storage in the other reservoirs. This rule will be approximated for each sequence by a function of the stored volume, as shown by line ABCDE in Figure 2. It should be stressed that the approximate release rule is "tailored" for sequence i. This means that the algorithm mimics the real time decision process.

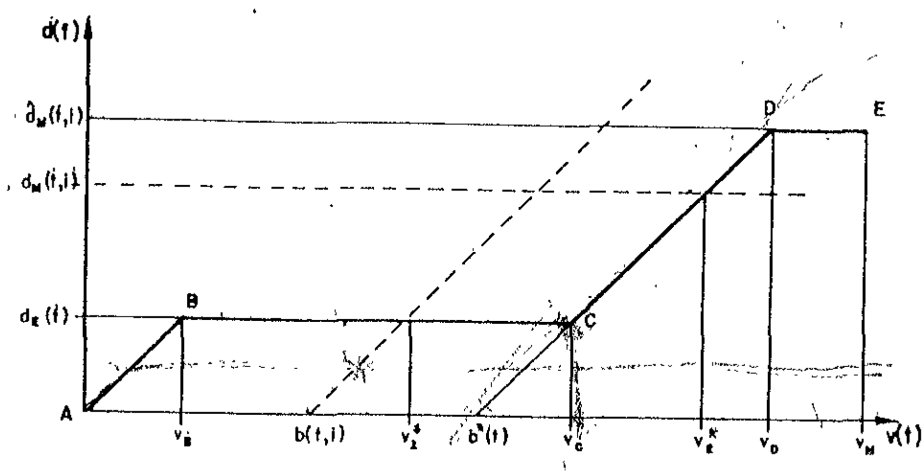

Figure 2. Approximate Release Rule (Solid Line) for Sequence i on Day t

In Figure 2, $d_E(t)$ represents the outflow necessary to meet the energy demand.

For a stored volume in the range $[0;v_B]$ there is not enough water to meet the energy demand. In the range $[v_B,v_C]$ the energy demand can already be met and the stored volume is low enough not to activate any flood constraint. In the range $[v_C,v_D]$ one has to yield more than the necessary to meet the load in order to keep the probability of flood events in the interval (t+1,h) equal to the target risk, $\alpha(t)$.

For a stored volume larger than v_D, one is bound by $\partial_M(t,i)$. This restriction is calculated by equation (2). In this case the probability of an emergency in the interval (t+1,h) is greater than $\alpha(t)$.

Let v_1^* be the interception between the approximate release rule and the critical release rule for sequence i. One can see that if $v(t)>v_1^*$ then $v(t+1)>c(t+1,i)$. The consequence is that some emergency will happen in the interval $(t+1,h)$, for the i-th sequence.

Let v_2^* be the interception between the actual safe release (not the forecasted one) and the approximate release rule. Again for sequence i, one can see that whenever $v(t)>v_2^*$ an emergency will occur exactly on day t due to the difference between the actual and the forecasted safe release.

The definition of $c(t,i)$ is met by equation (9).

$$c(t,i) = \min\{v_1^*, v_2^*\} \tag{9}$$

The Algorithm

Figure 3 describes the main aspects of the algorithm.

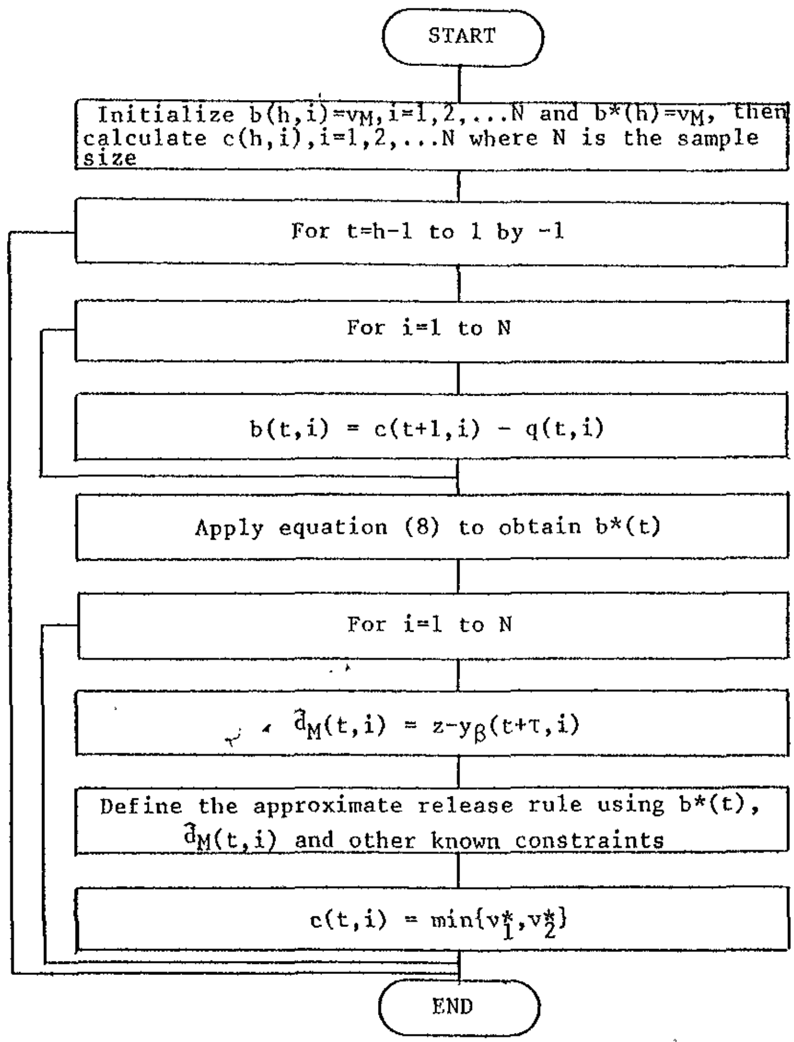

Figure 3: The algorithm

TRÊS MARIAS CASE STUDY

Três Marias is a hydroelectric power plant (388Mw) with a large reservoir ($19 \times 10^9 m^3$) located in the São Francisco River, Brazil. A flood constraint must be imposed to protect Pirapora, a city located 150 km downstream. Nearby flows greater than $z=4000 m^3/s$ will cause some damage to the city and were considered as the flood constraint. The travel time from the dam to Pirapora is approximately one day ($\tau=1$).

The flow coming from uncontrollable tributaries can exceed $2000 m^3/s$ during the wet season (December 1 to April 30). Gauges located on the main tributary can be used to provide on-line forecasts.

A constant value of 657 m^3/s is considered as the outflow necessary to meet the energy demand, i.e., $d_E(t,v(t)) = 657\ m^3/s,\ \forall(t,v(t))$.

Since the stochastic process "occurence of flows greater than z" can be well represented by a Poisson process (Shen and Todorovic, 1976) it is reasonable to define the "occurence of emergency" also as a Poisson process. Expression (10) will then represent the target risk.

$$\alpha(t) = 1-e^{\lambda(t-h)} \tag{10}$$

The return period for an emergency in (10) is given by $\{\alpha(0)\}^{-1}$. In this case, h=151 days.

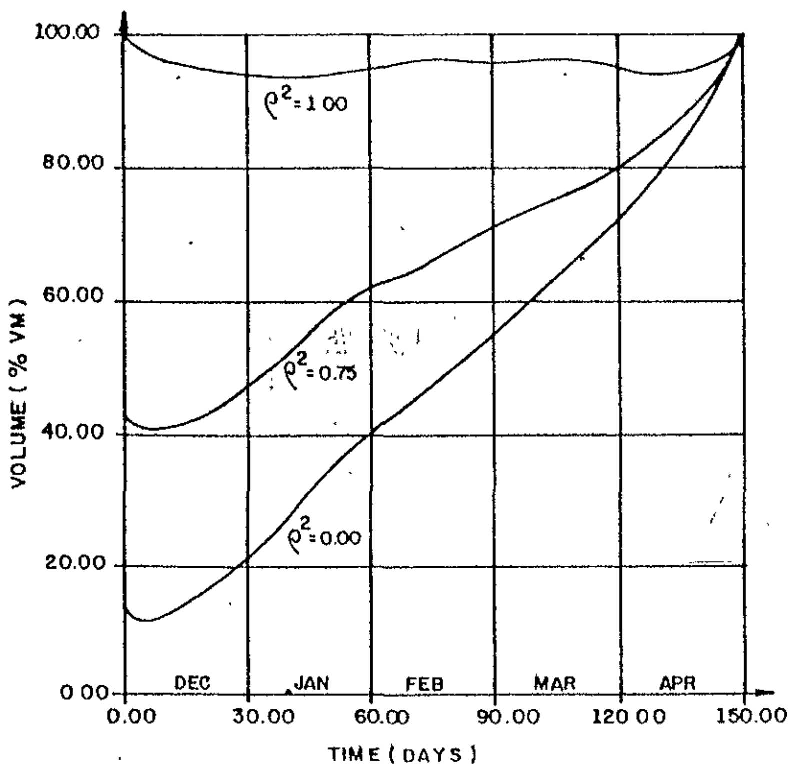

Figure 4. Evolution of b* for Different Forecasting Accuracy

Figure 4 shows the evolution of $b^*(t)$ calculated for a return period of 50 years and for different hypothesis of forecast accuracy. These results were obtained applying the algorithm over 10000 synthetic bivariate daily sequences (inflow to Três Marias and sum of uncontrollable tributaries). The adopted stochastic model is described by Kelman (1977). The daily release rule was approximated as shown in the previous section.

The forecasted maximum release $\hat{d}_M(t,i)$ was sampled together with each synthetic uncontrollable daily flow. Appendix A describes the sampling procedure in detail.

The value of ρ in Figure 4 corresponds to the correlation between the forecasted value and the real one: $\rho=0$ means "no information" and $\rho=1$ means "perfect information" ($\hat{d}_M(t,i) = d_M(t,i)$).

Figure 4 shows that the values of $b^*(t)$ increase with the degree of certainty as regards $d_M(t,i)$, measured by ρ^2. This means that the poorer the forecast, the more severe are the reservoir's yield restrictions.

Improvement of forecasting techniques helps to increase the probability of getting a filled up reservoir at the beginning of the dry season without increasing the risk of emergency. In order to evaluate the expected stored volume at the beginning of the dry season under the three values of ρ^2, a simulation study was performed with 1000 other sequences. The initial volume, $v(1)$, was set to 0.43 v_M in all simulations. This volume corresponds to $b^*(1)$ for $\rho^2=0.75$. Table 1 summarizes the results.

Table 1. Simulation Results for 1000 Sequences

ρ^2	$E[v(h)]$ ($\%v_M$)	EMERGENCIES (%)
1.00	61.15	0.03
0.75	57.83	2.5
0.00	36.97	7.6

CONCLUSIONS

1) The output of the algorithm is a set $\{b^*(t), t=1,2,\ldots,h\}$. The lower bound on the reservoir yield on each day t is equal to $\min\{0, v(t) - b^*(t)\}$.

2) The $b^*(t)$ are calculated in such a way that several features of real time operation are taken into account (forecasts, upper bounds on the yield and energy production).

3) The results of Figure 4 show that $b^*(t)$ increases with the degree of information about the uncontrollable flows.

4) The simulation study confirms that, conditioned to a specific initial volume, flood mitigation capability and the expected stored volume at the end of the wet season increase with ρ^2. These expected stored volumes can be converted into monetary units

(using the value of water for conservative purposes) and compared with the costs of the necessary forecast systems to provide the specific ρ^2.

APPENDIX A

FORECAST MODEL SIMULATION

The basic information provided by a forecast model is the conditional distribution of the variable of interest, Y, given the state of nature, X, which can be measured in advance.

Let (X,Y) be bivariate normal distributed and ρ the correlation between X and Y. In this case the conditional distribution $f_{Y|X}(y|X=x)$ is also normal distributed with moments

$$\mu_{Y|X} = \mu_Y + \rho \frac{\sigma_Y}{\sigma_X} (x - \mu_X) \quad \text{(A1)}$$

$$\sigma^2_{Y|X} = \sigma^2_Y (1 - \rho^2) \quad \text{(A2)}$$

Without loss of generality, let

$$\mu_X = \mu_Y \quad \text{(A3)}$$

$$\sigma_X = \rho\, \sigma_Y \quad \text{(A4)}$$

In this way,

$$\mu_{Y|X} = x \quad \text{(A5)}$$

As presented in the outline of the methodology, given the state of nature, X=x, a decision-maker may use a quantile, y_β, of the conditional distribution such that

$$P[Y>y_\beta | X=x] = \beta \quad \text{(A6)}$$

therefore,

$$y_\beta = \mu_{Y|X} + u_\beta\, \sigma_{Y|X} \quad \text{(A7)}$$

where u_β is the corresponding quantile of the unit normal.

Using (A2), (A5) and (A7)

$$y_\beta = x + u_\beta \sigma_Y (1-\rho^2)^{1/2} \quad \text{(A8)}$$

The algorithm presented in the outline of the methodology requires samples of (y, y_β). For the case study, y is the uncontrollable flow produced by the adopted stochastic model. The value y_β were obtained using the conditional distribution $f_{X|Y}(x|Y=y)$, a normal distribution with mean $\mu_Y + \rho^2(y-\mu_y)$ and variance $\rho^2\sigma_Y^2(1-\rho^2)$.

Using (A8), the equation to obtain y_β is

$$y_\beta = \mu_Y + \rho^2(y - \mu_Y) + \rho\sigma_Y(1 - \rho^2)^{1/2}\,\varepsilon + u_\beta\sigma_Y(1 - \rho^2)^{1/2} \qquad \text{(A9)}$$

where ε is sampled from the unit normal distribution.

The log transformation of the incremental flows (Y) was applied to achieve normality. u_β was set to 2.33 which is the corresponding value of the observed maximum incremental log-flow of the historical record.

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