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Abstract We describe our work in developing decision support tools to manage large international rivers. This is a complex environmental decision making problem due to the presence of multiple objectives stemming from multiple uses of the reservoirs (energy production, irrigation, flood protection, . . .), several sources of uncertainty (inflows, water demand, evaporation, . . .), long-term effects of decisions, . . . In comparison with other methodologies applied to solve operational problems, decision analysis has provided effective means to model preferences and beliefs of managers, leading to complex stochastic dynamic programming problems. To solve them, we have introduced novel computational strategies. The practical success of our approach stimulated us to develop BayRes, an interactive and integrated Decision Support System for solving operational control problems for reservoir management. Recent improvements in BayRes will be also discussed.

Keywords: Environmental Decision Making, Large River Management, Decision Analysis, Decision Support Systems.

1 INTRODUCTION

The literature dealing with reservoir operations typically identifies the solution of the reservoir operation problem with a specific technique applied to an optimization problem. This leads to the false conclusion that the reservoir operation task can be solved by direct application of the optimization method described in a particular paper. This "technique-focused" approach fails to present a comprehensive framework necessary to tackle reservoir operation problems without too many simplifying assumptions. The most common deficiency of "technique-focused" approaches boils down to a lack of mechanism for using available (incoming) information about inflows, users' demands and preferences, thus limiting the use of up-to-date information concerning operating conditions of the reservoir.

In this paper, we shall present methods and tools to solve some problems associated with the management of large international rivers. Our approach considers all the information available at each decision point, and we have found that Decision Analysis is capable to address real life problems and pro-

vides constructive results and solutions.

2 OPTIMIZATION OF THE MULTIOBJECTIVE CONTROL POLICY FOR LAKE KARIBA

The Zambezi river is situated at the South of the Equator, between 12° and 20° S latitude, and it is the largest of the African rivers flowing into the Indian Ocean. Its length is around 2 500 km from its source in the Central African Plateau to the Indian Ocean (see Balon et al.[1974]; Balek[1977]). Its total catchment is about 1 300 000 km². Eight countries share it, but the "major shareholders" are: Botswana, Zambia and Zimbabwe. Although the catchment possesses large development potential, the main water uses have been limited to the construction of three large hydropower schemes: Kariba and Cahora Bassa on the Zambezi itself, and Kafue Gorge and Itezhitezhi on the Kafue river, one of Zambezi main tributaries. The research efforts described in this paper are focused on Kariba due to its economic importance and availability of reach hydrological data.

The management of the Kariba scheme has been traditionally based on a rule curve, which relates the release from the reservoir to the actual amount of water stored at a given period of time. This curve gives a prior of the desired storage volume for every month of the year. According to such curve, the storage should gradually drop down between July and January, to provide sufficient storage for the annual flood, which is expected to fill the reservoir in the following months.

The optimal control policy should have two performance criteria: minimization of the maximum value of monthly energy deficit; and minimization of the maximum value of the total monthly release. Note the complexity of the problem as both criteria are conflictive: reducing monthly energy deficit requires higher releases, whereas minimization of total monthly releases require lower releases.

The approach we shall show in the next section was proposed (see Ríos Insua et al.[1995]) as an attempt to answer the question of whether the methods and methodology offered by Decision Analysis are capable to capture and adequately address such aspects of reservoir systems operation, like conflicting multiple objectives, dynamics and uncertainty.

Decision theory, see French et al.[2000] for an introduction, is implemented from an engineering point of view, with the aid of Decision Analysis (Clemen[1997]), giving coherent support to decision making through a rational framework that facilitates the solution of complex problems through an iterative cycle, called the Decision Analysis Cycle, based on: 1) *problem structuring*, identifying decisions, alternatives, states of nature, consequences and its relations, 2) *belief modelling*, the decision maker beliefs are encoded in a probabilistic model, 3) *preference modelling*, the decision maker preferences are encoded in an utility model, 4) *maximization of expected utility*, the maximum expected utility alternatives are identified, and 5) *sensitivity analysis*, studying the effects of different model assumptions and assessments to verify their consistence and detect whether new structure or further refinement is needed.

3   APPLYING DECISION ANALYSIS TO DEVELOP OPERATING POLICIES FOR THE LAKE KARIBA SCHEME

Our methodology, to deal with multiobjective stochastic problems for monthly planning reservoir system management (see Ríos Insua et al.[1997]),

differs significantly from traditional methodologies, which adopt a stationary view of the world, since it allows to take explicitly into consideration a dynamic character of the inflow processes.

Key issues of this methodology are: 1) the definition of flexible water release policies; 2) the use of Bayesian forecasting models for predicting future inflows; 3) a careful modelling of decision maker preferences, which include a term reflecting deviation from a pre-defined *reference trajectory* as we shall explain in more detail below; 4) development of heuristics to provide policies for approximate the maximization of expected utility; and 5) thorough checking of the policies through sensitivity analysis, to provide additional modelling insights.

3.1   The Methodology

The aim of the control policy is to determine at every discrete moment of time (for instance once a month) controls $u_{t+1}, \ldots, u_{t+k}$, that is, volumes of water to be released, where k is the planning horizon and t is the current time. Usually there can be distinguished several kinds of releases associated with various operational purposes, e.g. for hydropower generation, irrigation, flood control, spill, ... so that $u_t = (u_t^1, u_t^2, \ldots, u_t^l)$, where u_t^l denotes the volume of water released for purpose l at time t.

Information about the inflow process is given in the form of a predictive density $h(i_{t+1}, \ldots, i_{t+k}|D_t)$ determined based on analysis of historical data records. The predictive density specifies a forecasting model for inflows i, given the history D_t until time t. A preference model F, showing the consequences $c(u, i)$ associated with releasing u when the inflows are i, is given to allow the evaluation of consequences (impacts) of releases u. The storage at time t will be denoted s_t. An evaluation of the final state of the reservoir is given through a function G. Then, at a time t, the reservoir management planning problem for k periods ahead consists of finding controls $u_{t+1}, \ldots, u_{t+k}$ that maximize the expected utility

$$
\int \left(\sum_{j=1}^{k} F(c(u_{t+j}, i_{t+j})) + G(s_{t+k+1}) \right)
$$
$$
h(i_{t+1}, ..., i_{t+k}|D_t)di_{t+1}...di_{t+k} \quad (1)
$$

while taking into account the dynamics of the reservoir system, constraints over controls and reservoir storages. Typical constraints would include bounds on types of releases, bounds on maximum and minimum allowed reservoir storages, and con-

tinuity conditions relating storages at consecutive times given inflows, releases and evaporation:

$$s_{t+1} = s_t - e_t + i_t - \sum_l u_t^l,$$

where e_t is the evaporated volume at time t.

The above framework, to be applied for large reservoirs such as Kariba or Cahora which were considered in our studies, would require a 36 month or longer planning horizon. This long-term planning problem becomes computationally unmanageable, as a long-term stochastic dynamic programming problem has to be solved, and the evaluation of each control requires a high dimension integral. Additionally, the uncertainty about the inflow process rapidly propagates through considered time horizon. Although for problems with shorter horizons, stochastic programming provides appropriate computational and/or approximation schemes (see Birge et al.[1997] for a review, and Carlin et al.[1997] for alternative approaches based on forward simulation), an alternative strategy has to be adopted for our problem. A *reference trajectory* was used, which assumes availability of a "reference" storage level for each period. Then, the problem (1) can be reformulated as

$$\int \big(F(c(u_{t+1}, i_{t+1}) + \delta(s_{t+1}, s_{t+1}^*))$$
$$h(i_{t+1}|D_t) di_{t+1}, \quad (2)$$

where $\delta\big(s_{t+1}, s_{t+1}^*\big)$ represents the deviation of the final storage s_{t+1} from the reference storage s_{t+1}^*. Intuitively speaking, if reference storages are defined in such a way so as to account for the dynamic aspects of the problem, we would not loose too much with this modified "myopic" approach.

To compute the *reference trajectory*, we use a deterministic version of the problem (1), with inflows fixed at their predictive expected values $\bar{i}_{t+j}$. We use the same dynamics and constraints on storages and controls, and select an initial volume s_0. The objective function to be maximized is then

$$\sum_{j=1}^{k} F(c(u_{t+j}, \bar{i}_{t+j})) - \rho\,(s_{t+k+1} - s_0)^2$$
$$(3)$$

The optimal solution of (3) provides a *reference trajectory* $(s_{t+1}^*, \ldots, s_{t+k+1}^*)$. The (deterministic) dynamic programming problem (2) may be solved using discrete dynamic programming.

3.2 Forecasting methodology

An essential step in our approach is the development of an inflow forecasting model. Numerous recent modelling and computational enhancements have made DLMs (Dynamic Linear Models) readily available for applications, see West et al.[1997]. Berger et al.[1997] describe many of their advantages for hydrological modelling.

The aim of forecasting is to determine, at instant t, the next k values of the inflow (or a transformation of it), say y_t, from the instant $t + 1$ to instant $t + k$, given the available information D_t. For that we use DLMs which, in their simplest formulation, have the following structure for every instant of time $t = 1, 2, 3, \ldots$:

- *Observation equation:*

  $$y_t = F_t z_t + v_t, \quad v_t \sim N(0, V_t)$$

  where y_t denotes the observed value, which depends linearly on the state variables z_t, perturbed by a normal noise.

- *System evolution equation:*

  $$z_t = G_t z_{t-1} + w_t, \quad w_t \sim N(0, W_t)$$

  describing the evolution of the state variables, linearly dependent on the variables in the previous state plus a random perturbation.

- *Initial information:*

  $$z_0 | D_0 \sim N(m_0, C_0)$$

  describing the expert's prior beliefs.

The error sequences v_t and w_t are independent, and mutually independent. Moreover, they are independent of $(z_0 | D_0)$.

A basic advantage of DLMs is that they allow modelling features usual in hydrological time series like trend and seasonal patterns, and permit the incorporation of covariates, such as rainfall for inflows, based on the *superposition principle* (West et al.[1997]). The *superposition principle* states that linear combinations of independent DLMs provide a DLM. As a consequence, we use a model building strategy based on blocks (depending on the forecast horizon), representing trends, seasonal patterns, dynamic regression (if covariates are available), and, if required, an autoregressive term to improve short term forecasting.

3.3 Preference modelling

A preference model is required to evaluate the consequences of a decision. This estimation is not straightforward because sometimes the consequences have no obvious measurement scale. Moreover, in our context we shall have to face multiple attributes and uncertainties. A multiattribute utility function permits comparison between complex alternatives through the maximum expected utility principle.

We fit single-attribute utility functions comparing lotteries like

$$\begin{pmatrix} \alpha & (1-\alpha) \\ c & d \end{pmatrix} \forall \alpha \in [0,1]$$

This lottery represents a case in which we obtain c with probability of α and d with $(1-\alpha)$. If we make $c = x^*$ and $d = x_*$, where x^* and x_* are the best and the worst results for the attribute modeled, using the *equivalent probability method* and normalizing the utilities to $u(x_*) = 0$ and $u(x_*) = 1$, there is a quantity x_j, such that $u(x_j) = \alpha_j$, for $0 < \alpha_j < 1$. This method is used to determine the preference relationship **R** in

$$\begin{pmatrix} (1-\alpha) & \alpha \\ x_* & x^* \end{pmatrix} \mathbf{R} \begin{pmatrix} 1 \\ x_i \end{pmatrix}$$

All the elements except α are fixed and **R** represents the relations between both lotteries. The decision maker should provide his opinions about α until **R** represents indifference ($\sim$). In this case, we obtain that $u(x_i) = \alpha$.

In our reservoir problem, we have found that a flexible class of utility functions is composed of concave-convex functions. The specific version used, for increasing functions, is

$$a_{i1} - b_{i1} exp(-c_{i1}x), \text{ for } x < x_0$$
$$a_{i2} + b_{i2} exp(c_{i2}x), \text{ for } x \geq x_0$$
$$b_{i1}, b_{i2}, c_{i1} \text{ and } c_{i2} \geq 0 \qquad (4)$$

Once we have enough utility values ($u(x_j) = \alpha_j$), obtained as showed above, we estimate the shape parameters, $a_{i1}, a_{i2}, b_{i1}, b_{i2}, c_{i1}, c_{i2}$, to fix the utility function.

For a multiattribute problem, we use a weighted additive utility function. E.g., if there are two types of releases and n objectives,

$$F(u_1, u_2, i) = \lambda_1 f_1(u_1, u_2, i) + \cdots$$
$$+ \lambda_n f_n(u_1, u_2, i)$$

To obtain the $\lambda_1, \ldots, \lambda_n$ weights, we follow a similar approach, i.e we ask the decision maker until, for a specific attribute x_i, she is indifferent between the following lotteries

$$\begin{pmatrix} (1-p) & p \\ (x_{1*}, .., x_{i*}, .., x_{n*}) & (x_1^*, .., x_i^*, .., x_n^*) \end{pmatrix} \sim$$
$$\begin{pmatrix} 1 \\ (x_{1*}, .., x_i^*, .., x_{n*}) \end{pmatrix}$$

Then we obtain that $\lambda_i = p$.

3.4 Optimization

Having the forecasting model (described in section 3.2), the preference model (described in section 3.3) and the *reference trajectory*, we will look for controls to maximize the expected utility, for example, for each month. For simplicity, the optimization procedure used is described assuming that we have only two types of releases u_{1t}, u_{2t}. The problem to be solved is, therefore:

$$\max \ \Psi(u_1, u_2) = \int F(u_1, u_2, i) h(i) \mathrm{d}i \quad (5)$$
$$\text{s.t. } 0 \leq u_1 \leq m_1$$
$$0 \leq u_2 \leq m_2$$

where $\Psi(u_1, u_2)$ is the expected utility associated with controls u_1, u_2 and m_1, m_2 are the upper bounds for the releases respectively.

Two problems arise with the objective function to be maximized (5) due to it cannot be expressed, in general, in explicit form. First, difficulties with function evaluation. To deal with them, we use *Monte Carlo integration* approximation. Second, numerical difficulties with maximization of the objective function. To deal with them, the *Nelder-Mead algorithm* was used, as it requires only evaluation of the objective function and is rather robust in low dimension problems. See Palomo[2000] for more details in the solution of these problems.

3.5 BayRes

The implementation of the methodology described in previous sections is far from being simple. Its success in solving the Kariba and Cahora Bassa reservoir management problem (Ríos Insua et al.[1997]) and (Ríos Insua et al.[1995]) has led to the development of BayRes, a decision support system that combines elements of the approach presented here into one consistent framework to facilitate its application. Silver [1991] suggests that a Decision Support System (DSS) is a computer system

that tries to affect how people make decisions. We prefer to call DSS to a computer system that supports the decision making process, helping decision makers to explore the implications of their judgments in order to make decisions based on understanding of underlying assumptions, available information and consequences of plausible decisions.

BayRes has been created as a decision support system for reservoir operations, supporting all phases of the decision analysis process. It includes, embedded in a user-friendly windows based interface:

- a module to load historical and new data from their sources, typically a text file, into the system,

- a module to build a forecasting model, making easier the construction of the model, say for example, specification of the DLM process or data analysis,

- a module to build a preference model, including the computation of a *reference trajectory*,

- an optimizer and

- several sensitivity analysis tools.

The features of the application and its operation (see Palomo[2000] and Vallejo[2000] for a complete description of the implementation) are described and controlled through several windows. From the main menu you can launch one of the three different modules depending on the stage you are in the process: loading data, building the forecasting model, building the preference model or using sensitivity analysis. As this is not a sequential process, each module can be launched at a time with no order predefined except, of course, that optimizing and sensitivity tools require a previous model to work on it.

The preference model has the following steps: 1) Introducing the number of attributes and their characteristics maximum value, minimum value, . . . , 2) obtain some values of the utility function through lotteries for each attribute, 3) fit the different utilities function to a concave-convex or convex-concave family depending on the monotonicity properties, 4) obtain the weights of each utility function into the general additive multiattribute utility function, 5) construction of the general additive multiattribute utility function.

Figure 1 shows an example of the utility functions family used in the preference model for increasing preference (see the expression in (4)).

As a result of the optimization module, BayRes shows different charts for the control policy in the next k periods. In our example, these consist of monthly releases through spillgates and turbines, energy produced each month and total amount of water released each month.
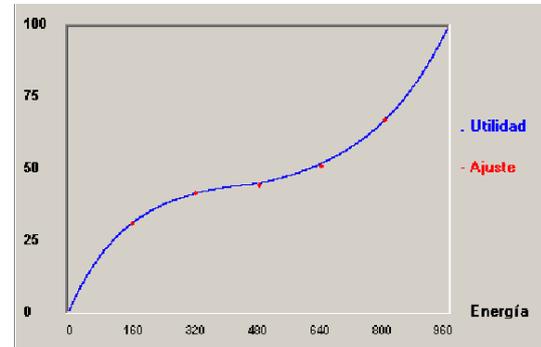

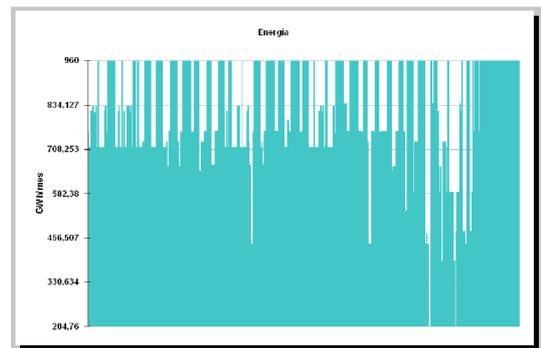Figure 1: Example of concave-convex increasing utility function built with BayRes.

Figure 2: Example of the control policy obtained after the optimization process.

BayRes provides capabilities to modify the suggested control policy as external input arrives. For example, its forecasting module allows for interventions, illustrating a principle of *management by exception*: a set of models is routinely used for processing information, making inferences and predictions, and making decisions, unless exceptional circumstances arise. Examples would include a sudden rainfall, a big release from an upstream reservoir, or the detection of a wet period. In such cases, the system is open to external (user-initiated and user-performed) interventions, typically by inclusion of additional subjective information. As

described in West et al.[1997], those interventions may be included formally within the DLM framework.

3.6 Further work on BayRes

The current version of BayRes focuses on single reservoir operation. We are developing a new release of it considering a multireservoir operation. Also, we are implementing new algorithms such as a modern *Nelder-Mead* type algorithms, multiplicative utility functions and stochastic programming.

Following object oriented programming philosophy, we are recoding the software into Java objects. This work will make easier further improvements and connection with external systems.

BayRes is available to be downloaded from the following web address: *http://bayes.escet.urjc.es/software/index.html*

4 CONCLUSIONS

The main contribution of our research to the field of water resources, and to the general theory of decision making, is a systematic and concise approach to dealing efficiently with the ever increasing complexity of the systems found in the natural environment. We had demonstrated that our approach provides good foundations to cope with this goal.

With the current political setting in the riparian countries, many options about future water use within the catchment now seem feasible. The real value of the decision support system may now be assessed, through simulating various possible water use scenarios in future both within and outside of the Zambezi river basin.

The DSS developed, BayRes, has demonstrated good results so it can be extended to other scenarios until a general DSS for reservoir management is obtained.

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