Deriving efficient reservoir operating rules using flexible stochastic dynamic programming

A. Tilmant, E. Persoons & M. Vanclooster
Dept of Environment, Science and Land Use Planning, Université Catholique de Louvain, Louvain-la-Neuve, Belgium

Abstract

Reservoir operation models traditionally require the transformation of all release consequences into one single monetary unit. This approach clearly shows its limitations when a variety of environmental, social, and political consequences cannot (or should not) be converted to monetary terms. As a consequence of its inability to consider all operating objectives, the traditional approach solely involves some stakeholders, making difficult the social acceptance of the release rules. This paper presents a new optimization approach for deriving efficient reservoir operating rules in a multiparticipatory decision-making framework. By considering the optimization problem as a multistage flexible constraint satisfaction problem, we are able to (1) incorporate decision makers (DM) and water users' preferences on the solution, and (2) to relax the set of possible solutions so that partially feasible solutions can also be examined. In addition, trade-offs between conflicting objectives, as well as between immediate and future consequences associated with a release decision, are also explicitly taken into account so as to reach the best system performance. Operating objectives are considered as the flexible constraints of a fuzzy stochastic dynamic program (FSDP) over an unbounded planning horizon. The proposed model can employ different hydrologic information to describe the temporal persistence found in most hydrologic time series. We illustrate this approach with a multipurpose reservoir located in Morocco, where the main operating objectives are irrigation, flood control, and the production of hydroelectricity. This paper also examines the underlying issues of aggregating unequal objectives, capturing decision makers' preferences, allowing and determining the level of positive compensation (trade-off) amongst different degrees of constraint and goal achievements, implementing FSDP-derived results in real-time or simulated operation.

1 Introduction

Dynamic programming (DP) is an optimization approach that is well suited to solve multistage decision-making problems such as reservoir operation. The reason for this success lies in the versatility of DP and its ability to be tailored to the system. For example, stochastic DP (SDP) formulations are traditionally adopted to deal with the stochastic nature of the inflows. Yeh [1] provides a state-of-the-art review of the applications of DP and SDP in reservoir optimization problems. Example of applications of SDP models can be found in Stedinger et al. [2], Kelman et al. [3], Tejada-Guibert et al. [4]. In the SDP model, release decisions are given in each time period as a function of both the storage level at the beginning of the time period, and the hydrologic state variable(s).

Most of the studies found in the literature have been developed to solve hydro-dominated systems. Consequently, their objective functions stress on hydropower generation. Important secondary economic objectives are generally incorporated into the optimization algorithm by means of a penalty or loss function reflecting opportunity costs (Datta and Burges [5]). Stedinger et al. [2] derive optimal operating policies for a multipurpose reservoir using a loss function with specific penalties and targets for flood control, irrigation and power generation. In Tejada-Guibert et al. [4], the energy production of a multireservoir system is penalized when water and/or power targets are not met. The use of loss functions for apprehending the multiobjective nature of reservoir resources presents serious limitations. First, it requires the transformation of all release consequences into one single monetary unit, which is inconsistent with most practical applications. As a matter of fact, the management of most water resource systems affects a variety of factors; some of them cannot be converted to monetary terms (wildlife conservation, wetlands enhancement, flood hazard reduction, subsistence agriculture, ...). It has to be noted here that these objectives are gaining importance with the increase attention towards environmental issues and the need for sustainable reservoir operation (Loucks et al. [6]). Secondly, it is widely recognized that the estimation of the penalty coefficients, which are selected by the DM only, is imprecise and subjective. So, traditional optimization models suffer from (1) the inability to explicitly consider all release consequences and (2) a lack of public participation.

A new optimization paradigm is therefore needed for handling the above-mentioned issues. Recently, researchers and DM have paid particular attention to fuzzy techniques. Fontane et al. [7] use a fuzzy DP formulation to derive operating policies. Monthly operating objectives and the end-of-the year goal are represented by fuzzy sets. The membership functions are constructed from surveys of DM and water users familiar with the system. This approach handles the vagueness associated with the consequences of a release decision, but the effectiveness of the release rule becomes questionable if the hydrologic regime is highly variable. Teegavarapu and Simonovic [8] present a methodology for handling the imprecision involved in the definition of loss functions. Tilmant et

Transactions on Ecology and the Environment vol 48, © 2001 WIT Press, www.witpress.com, ISSN 1743-3541

al. [9] develop a flexible (fuzzy) SDP (FSDP) model for deriving optimal reservoir operating policies over an unbounded planning horizon. Membership functions are also based on water users' preferences. The aggregation of the fuzzy sets is achieved by a weighted sum followed by a "fuzzy and" operator so that trade-off between immediate and future consequences can also be taken into account. This FSDP approach is generalized and applied to a multireservoir system in Tilmant et al. [10]. They show that the meaning of the aggregation may have a major impact on the performance of the system and that more attention should be paid to the least satisfied objective.

This paper surveys refinements of the FSDP model and discusses the implementation issues. Sustainability issues, such as public participation and the estimation of a large spectrum of release consequences, are further analyzed. These concepts are illustrated with a real case study located in Morocco, where the main operating objectives are irrigation, flood control, and the production of hydroelectricity. This paper is organized as follows. The FSDP model is presented first. Then, FSDP models with weighable and unweighable fuzzy goal are discussed. The issue of the estimation of the compensation level is examined next. Those concepts are then illustrated with a case study. Finally, concluding remarks are given.

2 Flexible stochastic dynamic programming

In the classical SDP formulation, an objective function has to be optimized subject to a set of constraints describing the physical and economical limitations of the system. The objective function obviously plays the role of some performance indicator, which associates with each alternative the gain (or loss) resulting from the choice of that alternative. The constraints, on the other hand, have the effect of limiting the set of feasible solutions. The transition from one stage to the next is controlled by the continuity equation of the reservoir:

$$S_{t+1} = S_t + Q_t - R_t - e_t \qquad (1)$$

where t is the index of time period; S_t is the volume in storage at the beginning of period t; Q_t is the total inflow to the reservoir during time period t; R_t is the release during period t, and e_t are the evaporation losses during period t.

In the FSDP approach, the flexible constraint refers to a class of constraints that can be partially fulfilled, i.e. some degrees of constraint violation are permitted but its full satisfaction is preferred (Dubois and Fortemps, [11]). The degree to which a solution x satisfies a constraint C will be described by the membership grade $\mu_C(x) \in [0,1]$.

The fuzzy goal is a fuzzy set whose membership function $\mu_G : X \to [0,1]$ plays a role similar to that of the objective function in the conventional optimization problem.

Using the above concepts of fuzzy constraint and goal, the decision-making in a fuzzy environment consists in aggregating the constraint(s) and the goal(s) to form a suitable decision function *D*. Then, the alternative that "best" satisfies the decision function is selected.

At each stage *n* (time *t*), the performance of the reservoir is evaluated by *K* unequal objectives $O_t = \{O_{1,t}, O_{2,t}, \ldots, O_{K,t}\}$, which reflect the various concerns such as the degrees to which current and future operating objectives (services) are satisfied or affected by the current release decision R_t. Let $\mu_{O_{i,t}}(S_t, Q_t, R_t) \in [0,1]$ be the satisfaction degree of objective $O_{i,t}$ by the alternative (S_t, Q_t, R_t). Assume $\omega_{i,t}$ is a non-negative number indicative of the relative importance of the objective $O_{i,t}$ during time period *t*. Assume *f* a function for including the relative importance of each objective. Then, at stage *n* (time *t*), the evaluation vector $\boldsymbol{O}_t \in \mathbb{R}^{K\times 1}$ is:

$$\boldsymbol{O}_t = [\mu^{eff}_{O_{1,t}}(.)\ \mu^{eff}_{O_{2,t}}(.)\ \ldots\ \mu^{eff}_{O_{K,t}}(.)]^{\tau}$$

where $\mu^{eff}_{O_{i,t}}(.) = f(\mu_{O_{i,t}}(.), \omega_{i,t})$ is the effective satisfaction of objective $O_{i,t}$ during period *t*, and τ is the transpose operation.

The fuzzy decision set D_t results from the aggregation $\odot : \underbrace{[0,1]\times[0,1]\times\ldots\times[0,1]}_{K\ times} \rightarrow [0,1]$ of the *K* objectives $O_{i,t}$, $i = 1, 2, \ldots, K$. This aggregation corresponds to some operation on *K* fuzzy sets, and more specifically on the *K* membership functions $\mu^{eff}_{O_{i,t}}(.)$. The interpretation of the aggregation is generally left to the DM, and can therefore be tailored to the decision-making problem. For example, if we desired all the objectives be satisfied, a common operator would be the minimum, which corresponds to the logical "and". At the other extreme is the situation in which the DM wants any of the objectives be satisfied. This corresponds to the logical "or", and the max-operator is usually adopted.

Considering the reservoir operation problem as a periodic, infinite-horizon, and stationary problem, the optimal operating policy can be found by the recursive solution of a flexible stochastic dynamic program (FSDP):

$$\begin{aligned}\mu^*_{G_n}(S_t, H_t) = E_{Q_t|H_t}[\bigvee_{R_t}\{\mu^{eff}_{O_{1,t}}(S_t, Q_t, R_t) \odot \mu^{eff}_{O_{2,t}}(S_t, Q_t, R_t) \odot \ldots \\ \odot\, \mu^{eff}_{O_{K-1,t}}(S_t, Q_t, R_t) \odot E_{H_{t+1}|H_t, Q_t}\, \mu^*_{G_{n-1}}(S_{t+1}, H_{t+1})\}]\end{aligned} \quad (2)$$

subject to

$$\max[R_{\min}, S_t + Q_t - S_{\max}] \le R_t \le \min[R_{\max}, S_t + Q_t - S_{\min}]$$

where

n = number of stages remaining until the end of the planning horizon; t = index of period; S_t = storage at the beginning of period t; H_t = hydrologic state in period t; Q_t = inflow during period t; R_t = release during period t; $\mu^*_{G_n}(S_t, H_t)$ = expected membership grade from the optimal operation of the system from the current period t to the end of the planning horizon given that the system's status in period t is (S_t, H_t); $\mu^{eff}_{G_{n-1}}(S_{t+1}, H_{t+1})$ = membership grade of the K^{th} objective = fuzzy goal = effective satisfaction degree associated with the optimal operation of the system from the next period t+1 to the end of the planning horizon given that the system's status in period t+1 is (S_{t+1}, H_{t+1}); $\mu^{eff}_{O_{i,t}}(S_t, Q_t, R_t)$ = membership grade of the i^{th} objective = i^{th} flexible constraint = effective satisfaction of objective $O_{i,t}$ during period t given the alternative (S_t, Q_t, R_t); E = expectation operator; $\odot$ = aggregation operator; $\vee$ = maximum operator.

3 FSDP model with a weighable fuzzy goal

When the DM can simultaneously compare the objectives and estimate their relative importance, the implementation of (2) is fairly straightforward. The procedure requires the estimation of the criteria weights $\omega_{i,t}$. This can be achieved by using, for example, Saaty's method of pairwise comparisons (Saaty, [12]). Then the aggregation operator has to be selected. Several functions for including weights factors in conjunction with different aggregation operators are available in the literature to derive suitable decision functions. See for example Yager [13], Yager [14], Zimmermann [15], Kaymak and van Nauta Lemke [16]. One of the most common method is the weighted function in which the satisfaction degrees $\mu_{O_{i,t}}(.)$ are directly multiplied by their weighting coefficients $\omega_{i,t}$:

$$D_t(.) = \sum_{i=1}^{K} \omega_{i,t}\, \mu_{O_{i,t}}(.) \qquad (3)$$

This weighted function has been adopted by Fontane et al. [7], Tilmant et al. [9]-[10], Li and Lai [19]. Eqn (3) is the most common operator obtained from the generalized averaging operator (Kaymak and van Nauta Lemke [16]):

$$D_t(.) = \left[\sum_{i=1}^{K} \omega_{i,t}\, \mu_{O_{i,t}}(.)^s\right]^{1/s}, \; s \in \mathbb{R} \setminus \{0\} \qquad (4)$$

$$D_t(.) = \prod_{i=1}^{K} \mu_{O_i,t}(.)^{\omega_{i,t}}, \ s = 0 \tag{5}$$

The value of the parameter s can be modified to adjust the meaning of the aggregation. For positive value of s, the influence of the objectives that are best satisfied (high membership grade) increases in the decision function. For negative value of s, the decision function is more determined by the objectives that are less satisfied (low membership grade), and the decision-making becomes pessimistic. Tilmant et al. [10] develop an FSDP model (2) with the aggregation functions (4) or (5) to determine the best operating strategy for the hydropower system of the Uruguay River basin in Brazil. They also show that the traditional operator (3) doesn't necessarily generate equitable operating policies since it emphasizes to much on the most achieved objectives to the detriment of the least achieved ones.

4 FSDP model with unweighable fuzzy goal

Although it is relatively easy to compare the flexible constraints (the current operating objectives) and to identify their specific priority scores, the DM may feel uneasy to attach a preference to the goal, which reflects the future consequences associated with the decision. This is especially true when, for example, the DM don't have a clear idea of what the future will be due to a high hydrologic uncertainty. Under such circumstances, the aggregation of the constraints and the goal cannot be carried out simultaneously as in (4) or (5). Rather, the proposed alternative to the direct implementation of (2) and (4)-(5) relies on a two-step aggregation process: the flexible constraints are first aggregated using a weighted function to form a super constraint function, and then the fuzzy goal and the super constraint are combined using a compensatory intersection operator. The rationale behind this approach is that we want to form a suitable decision function from a fuzzy goal, a set of flexible and unequal constraints, while being consistent from a logical point-of-view.

The first aggregation is needed to include the relative importance of the flexible constraints only. Here, the super constraint function $\mu_{C,t}(.)$ is obtained from the well-known weighted function (3) with the K-1 flexible constraints $\mu_{C_i,t}(.)$ and their weighting coefficients $\omega_{i,t}$:

$$\mu_{C,t}(.) = \sum_{i=1}^{K-1} \omega_{i,t}\, \mu_{C_i,t}(.) \tag{6}$$

Then the super constraint $\mu_{C,t}(.)$ and the fuzzy goal $\mu_{G,n-1}(.)$ are aggregated to form a suitable decision function D_t using a compensatory intersection operator. The fact that we want to satisfy the super constraint *and* to attain the fuzzy goal motivates the use of an intersection operator. The latter is equivalent to the logical "and" and corresponds to the minimum operator or any t-norm.

However, as pointed out by Tilmant et al. [9], some level of positive compensation (trade-off) between the super constraint and the fuzzy goal must be taken into account so as to prevent the "Drowning Effect" (Dubois and Fortemps [11]). The use of a compensatory intersection operator also permits the inclusion of the relative importance of the fuzzy goal and the super constraint. Nevertheless, in most practical applications, a reliable estimate of the balance between immediate and future consequences is, a priori, difficult to establish. Considering the above-mentioned remarks, a convex combination between the super constraint and the fuzzy goal appears to be an attractive candidate. This parametric operator is linear combination of the max and the min in which the parameter can be modified so as to adjust the meaning of the aggregation (from the min to the max, i.e. from the logical "and" to the logical "or"). However, since the compensation is expected to be never complete, which would correspond to achievement of only one of the two objectives, we recommend the use of the "fuzzy and" operator. This "fuzzy and" operator is a convex combination between the min and the mean so that the domain is limited to the min-mean interval. It is close to the logical "and" and thus corresponds to the achievement of "almost" both objectives. At each stage n (time t), the decision function D_t is given by:

$$\mu_{D_t}(.) = \gamma\left\{\mu_{C_t}(S_t, Q_t, R_t) \wedge E_{H_{t+1}|H_t,Q_t}\,\mu_{G,n-1}(S_{t+1}, H_{t+1})\right\} + (1-\gamma)\frac{\mu_{C_t}(S_t, Q_t, R_t) + E_{H_{t+1}|H_t,Q_t}\,\mu_{G,n-1}(S_{t+1}, H_{t+1})}{2} \qquad (7)$$

where γ is the compensation parameter, $\gamma \in [0,1]$;

$\wedge$ is the min operator.

5 Estimation of the compensation level

The implementation of the FSDP model (2) with the aggregation functions (6) and (7) requires the determination of the level of compensation γ. Recall that, in some sense, γ allows us to adjust the balance between the achievement of the super constraint and the attainment of the fuzzy goal, or in other words, between the immediate and the future consequences. Although the optimal release decision is expected to lie somewhere at the intersection between both consequences, its precise location remains unknown. To handle this issue, we propose an approach based on a sensitivity analysis. Several FSDP models, each with a specific value of γ, are developed and implemented to simulate the system using historical or synthetic monthly flow series. Then, performance indicators such as the reliability of system operation are estimated from the simulated operation. A comparison of these indicators allows us to determine the compensation level γ that yields the most interesting performance. Note that the indicators must be chosen so as to reflect the concerns of the various groups of interest affected by the reservoir resource. Two different classes of indicators are available: the conventional and the unconventional ones.

Conventional performance indicators express the performance of the system in terms of target satisfactory states and/or economic criteria. The most desirable policy occurs when simulated performance is closest to the satisfactory states and criteria. For example, the reliability and the resiliency of system operation are conventional performance indicators that have been reported in many studies (Hashimoto et al. [18]; Datta and Burges [5]). Reliability is defined as the probability that a state of the system X_t is in satisfactory state S. Resiliency of a system operation is the probability of moving from an unsatisfactory state F at time t-1 to a satisfactory state S at time t.

Unconventional performance indicators, on the other hand, rely on the subjective satisfaction of water users and managers when the system enters in a particular state with a particular release decision. The subjective satisfaction can be obtained from the membership functions of the flexible constraints and the stationary fuzzy goal. Recall that a flexible constraint can be partially satisfied (or violated). Since the membership functions are constructed based on the assumption that the degree to which the constraint is satisfied is equivalent to the subjective satisfaction it generates, it appears natural to use the former to express the latter. So, generally speaking, a policy that yields on average a higher membership grade is preferred.

6 Assessment of membership functions

In the FSDP formulation (2), operating objectives are considered as flexible constraints, and mathematically encoded as fuzzy sets. The flexible constraints represent the operating objectives formulated in terms of fuzzy sets, where the membership function expresses the degree to which the states of the system fulfill particular definitions reflecting decision makers and water users' preferences. For example, optimal release policy should yield to *adequate agricultural water supply*, to *dependable flood control*, to *efficient hydropower generation*, to *adequate municipal water supply*, and to *sustainable future operations*; where each group of italicized words represents a fuzzy set.

A reliable definition of the membership functions associated with the operating objectives is a crucial point since the machinery of fuzzy mathematics directly relies on the membership functions of the fuzzy quantities. A simple and robust method for assessing the membership function is the so-called direct method. It consists in identifying the most and the least acceptable values that can take the variable of interest, whether it is the storage volume, the hydrologic state, and/or the release decision. A membership grade of 1 is assigned to the most acceptable values, whereas the least acceptable values receive a membership grade of 0. These two extremes are then linked by a sigmoid function so as to obtain a smooth curve.

7 Example : The Mansour Eddahbi reservoir

The Mansour Eddahbi reservoir is one of the major reservoir resources in southern Morocco. It is situated in the middle Drâa valley. This reservoir has a usable storage capacity of 535 10^6 m^3, and drains a watershed of 15 000 km^2 located mainly in the High Atlas. The Mansour Eddahbi reservoir supplies water to different consumers: (1) the farmers living in the 6 oases located downstream along the Drâa river via the local agency of the Ministry of Agriculture, (2) the municipality of Ouarzazate via the national water supply company, and (3) the national electricity company.

In terms of volume, the main water uses are irrigation, flood control and hydropower generation. In what follows, water supply won't be considered in the optimization algorithm. Moreover, since the hydrologic regime is characterized by significant variation in both monthly and annual flows, the relative importance of the future is difficult to estimate. Therefore, the FSDP model (2) with the aggregation functions (6) and (7) is developed with the following fuzzy objectives: *adequate agricultural water supply*, *dependable flood control*, *efficient hydropower generation*, and *sustainable future operations*. For the selected case study, water requirements for irrigation can be considered as fuzzy sets because of the difficulty to quantify them precisely due to both the heterogeneity between the irrigated areas and the lack of appropriate databases and techniques (Faouzi [19]). The representation of the second objective (flood control) by a fuzzy set is motivated by the inherent vagueness and subjectivity associated with the definition of satisfactory storage levels to be reached before and during the high flow season. The efficient hydropower generation is defined here as the ratio between the effective and the maximum production. Finally, the last objective says that the current release decision should not compromise future operations, and thus prevents "myopic" decisions.

The compensation level γ, which allows us to balance the achievement of the current operating objectives and the attainment of the fuzzy goal, is assumed independent of the time period and of the system's status. It is determined from simulated performance indicators using 100-year simulated monthly inflows sequence. These indicators are the reliability and the resiliency of system operation, each calculated with two satisfactory states: (1) the annual cumulative release, i.e. the amount of water released from September to August should be larger than 250 million m^3 (indicator #1) and (2) the end-of-the year storage volume, i.e. the amount of water in storage at the end of August, should be between 300 and 400 million m^3 (indicator #2).

Performance criteria are evaluated for γ ranging from 0 to 0.95 and displays on fig. 1. When little or no compensation is allowed (γ is close to 1), the FSDP model (2) converges very slowly due to the *Drowning Effect*. From the examination of fig.1, it can be seen that the most interesting value of γ is around 0.8. Optimal policy tables with $\gamma = 0.8$ should therefore be used for real-time monthly operation or for simulation.

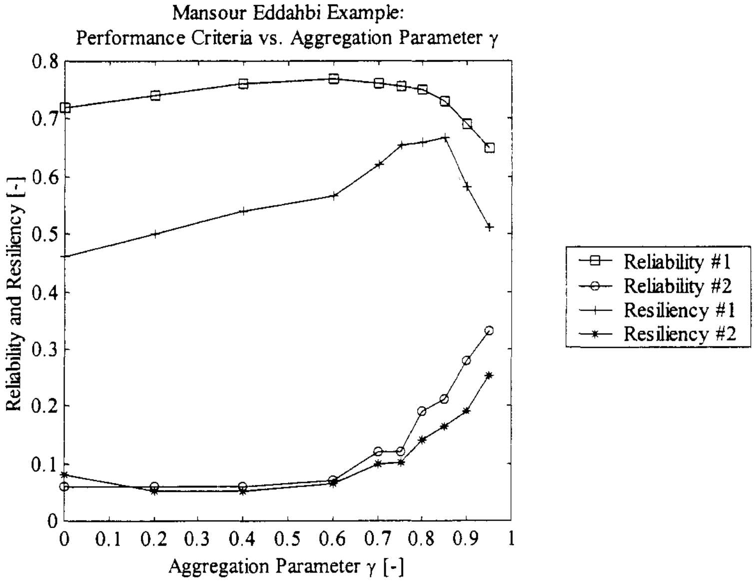

Figure 1. Reliability and resiliency of simulated operations for different aggregation parameters

8 Conclusions

This paper presents a flexible optimization approach for deriving efficient operating rules for multipurpose reservoirs characterized by economic and non-economic (intangibles) objectives. Therefore, the approach is well suited for situations where classical optimization techniques cannot be implemented due to the absence of information and/or methods for assessing the economic benefits (or losses) of system operation. Here, the use of fuzzy sets allows us to capture water user's and manager's preferences and expectations, which are then maximized by the FSDP algorithm. So, traditional economic performance indicators are replaced by the subjective satisfaction generated by the operation of the reservoir resource. It becomes therefore possible to explicitly take into account a variety of intangible objectives and to examine their impacts on the performance of the system.

References

[1] Yeh W. W-G., 1985. Reservoir Management and Operations Models: A State-of-the Art Review. *Water Resources Research* 21(12): 1797-1818.

[2] Stedinger J. R., B. F. Sule, and D. P. Loucks, 1984. Stochastic Dynamic programming Models for Reservoir Operation Optimization. *Water Resources Research* 20(11): 1499-1505.

[3] Kelman J., J. R. Stedinger, L. A. Cooper, E. Hsu, and S. Yuan, 1990. Sampling Stochastic Dynamic Programming Applied to Reservoir Operation. *Water Resources Research* 26(3): 447-454.

[4] Tejada-Guibert A., S.A. Johnson and J.R. Stedinger, 1993. Comparison of Two Approaches for Implementing Multireservoir Operating Policies Derived Using Stochastic Dynamic Programming. *Water Resources Research* 29(12): 3969-3980.

[5] Datta B. and S. Burges, 1984. Short-term, single, multiple-purpose reservoir operation: importance of loss functions and forecast errors. *Water Resources Research* 20(9): 1167-1176.

[6] Loucks D, E. Stakhiv and L. Martin, 2000. Sustainable Water Resources Management. *J. Water Resour. Plann. Manage.* 126(2): 43-47.

[7] Fontane D. G., T. K. Gates, and E. Moncada, 1997. Planning Reservoir Operations with Imprecise Objectives. *J. Water Resour. Plann. Manage.* 123(3): 154-163.

[8] Teegavarapu R.S.V. and S.P. Simonovic, 1999. Modeling Uncertainty in Reservoir Loss Functions Using Fuzzy Sets. *Water Resources Research* 35(9): 2815-2823.

[9] Tilmant A., L. Duckstein, M. Vanclooster and E. Persoons, 2000. Comparison of reservoir operating policies derived using fuzzy and non-fuzzy explicit stochastic dynamic programming. *Internal report*, Dpt. of Envr. Sc. and Land Use Plann., Univ. cath. de Louvain, Louvain-la-Neuve, Belgium.

[10] Tilmant A., P. Fortemps, M. Vanclooster, 2001. On the use of averaging operators in fuzzy stochastic dynamic programming. *Internal report*, Dpt. of Envr. Sc. and Land Use Plann., Univ. cath. de Louvain, Louvain-la-Neuve, Belgium.

[11] Dubois D. and P. Fortemps, 1999. Computing improved optimal solutions to the max-min flexible constraint satisfaction problems. *European Journal of Operational Research* 118: 95-126.

[12] Saaty T. L., 1977. A Scaling Method for Priorities in Hierarchical Structures. *J. Math. Psychol.* 15: 234-281.

[13] Yager R., 1978. Fuzzy Decision Making Including Unequal Objectives. *Fuzzy Sets and Sysems* 1: 87-95.

[14] Yager R., 1988. On Ordered Weighted Averaging Aggregation Operators in Multicriteria Decision-making. *IEEE Transactions on Systems, Man, and Cybernetics* 18(1): 183-190.

[15] Zimmermann H.-J, 1991. Fuzzy Set Theory and Its Application (2nd edition). Kluwer Academic Publishers, Norwell, Mass.

[16] Kaymak U., and H. R. van Nauta Lemke, 1998. A Sensitivity Analysis Approach to Introducing Weight Factors Into Decision Functions in Fuzzy Multicriterion Decision-making. *Fuzzy Sets and Systems* 97: 169-182.

Transactions on Ecology and the Environment vol 48, © 2001 WIT Press, www.witpress.com, ISSN 1743-3541

[17] Li L. and K. K. Lai, 2001. Fuzzy Dynamic Programming Approach to Hybrid Multiobjective Multistage Decision-making Problems. *Fuzzy Sets and Systems* 117: 13-25.

[18] Hashimoto T., J. R. Stedinger and D. P. Loucks, 1982. Reliability, Resiliency, and Vulnerability Criteria For Water Resource System Performance Evaluation. *Water Resources Research* 18(1): 14-20.

[19] Faouzi E.H., 1999. Diagnostic Hydrique de la Culture du Blé en Milieu Oasien, Ph.D. thesis, Univ. cath. de Louvain, Louvain-la-Neuve, Belgium.