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PREFACE

Analysis concerned with problems of the rational use of natural resources almost invariably deals with uncertainties with regard to the future behavior of the system in question. This uncertainty is due to the fact that the state of a complex system, such as those of practical interest, is always partially unknown. Thus, one of the major problems in real-time management is the selection of the most valuable information and its rational use in terms of systems performance.

For this reason one of the issues addressed during the Summer Study "Real-time Forecast Versus Real-time Management of Hydrosystems" organized by the Resources and Environment Area of IIASA in 1981, was the possibility of developing simple and heuristic methods for determining the value of information in multipurpose reservoir management. The research was mainly conducted with reference to the case of Lake Como for which a substantial amount of data were available. This paper is one of a series of IIASA publications based upon the results obtained during the study. It analyzes the value of information in real-time operation of multipurpose reservoirs and describes a simple operational scheme strongly based on the experience of the reservoir manager.

Janusz Kindler
Chairman
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ABSTRACT

This paper analyzes in quantitative terms the effectiveness of information in real-time operation of multipurpose reservoirs. For this, a simple and heuristic method strongly based on the experience of the manager is proposed and tested on the case of Lake Como (northern Italy). Particular attention is devoted to the possibility of evaluating the surplus of benefit due to the information available in real-time in addition to reservoir storage (e.g., snow cover, aquifer depth, and rainfall in the catchment). Moreover, a management scheme based on the direct use of the raw data is compared with a more sophisticated scheme using inflow predictors. Surprisingly, the first scheme, although more simple, performs better, thus justifying to a certain extent the little interest that practitioners sometimes seem to have for real-time forecasting techniques.

CONTENTS

THE VALUE OF INFORMATION IN RESERVOIR MANAGEMENT

1. INTRODUCTION

Many attempts have been made in the past few years to make efficient use of information in addition to reservoir storage (level) in optimizing the real-time operation of reservoirs. In particular, attention has been devoted to the problem of exploiting a reliable forecast of future inflows (see Gal 1979; Ambrosino et al. 1979; Unny et al. 1981; Toebes et al. 1981; Orwig and Fodrea 1981; Maidment and Ven Te Chow 1981; Helweg et al. 1982). It must be recognized however that reservoir managers often base their decisions directly on raw data, such as snow cover, precipitation in the reservoir catchment, actual water demand, and others, which give an indication of the future availability and need of resource.

Most of the proposed methods do not explicitly quantify the value of the extra information, since they simply cannot operate without it. On the contrary, the possibility of evaluating the surplus of benefit due to a surplus of information is very important, in particular when designing a real-time information system which can provide raw hydrometeorological data or elaborated information, such as inflow or meteorological forecasts, to the decision maker.

This paper analyzes in quantitative terms the effectiveness of information in real-time reservoir operation, using a heuristic approach, strongly based on the experience of the manager. Thus, the present method is, strictly speaking, only applicable to reservoirs which are already in operation. It suggests, however, some general considerations on the use of hydrometeorological data. In particular, a comparison between an approach which directly uses raw hydrometeorological data with a different one using inflow forecasting models shows a greater effectiveness of the first approach at least for the case examined.

The second section of the paper outlines the most important features of the decision-making process for reservoir management, while the third one suggests a general heuristic procedure for the best use of information in reservoir operation. Section 4 describes the application of the suggested procedure to a real case (Lake Como, northern Italy), while Section 5 discusses the results and their main implications.

2. FEEDBACK AND FEEDFORWARD MANAGEMENT SCHEMES

The operation of a multipurpose reservoir is a very complex decision making process which can be roughly described in the following way. The manager, during the year, tries to follow a predetermined reference schedule of levels x_t^* and releases r_t^* (from now on the index t indicates the day). Whenever the hydrological conditions in the basin deviate from the norm, managers are forced to deviate from their schedules in a way which is dependent upon the availability and need of resource at that particular time. Usually, they increase the release with respect to the schedule if more resource is available than in normal conditions, and reduce the release in the opposite case.

If the reservoir storage is a meaningful indicator of the total amount of water available, the decision-making process can be represented by the classical feedback control scheme of Figure 1, where x_t is the level of the reservoir at the beginning of the t-th day, r_t and a_t are release and inflow during the same day and the "controller" is uniquely indentified by an "algebraic" control law,

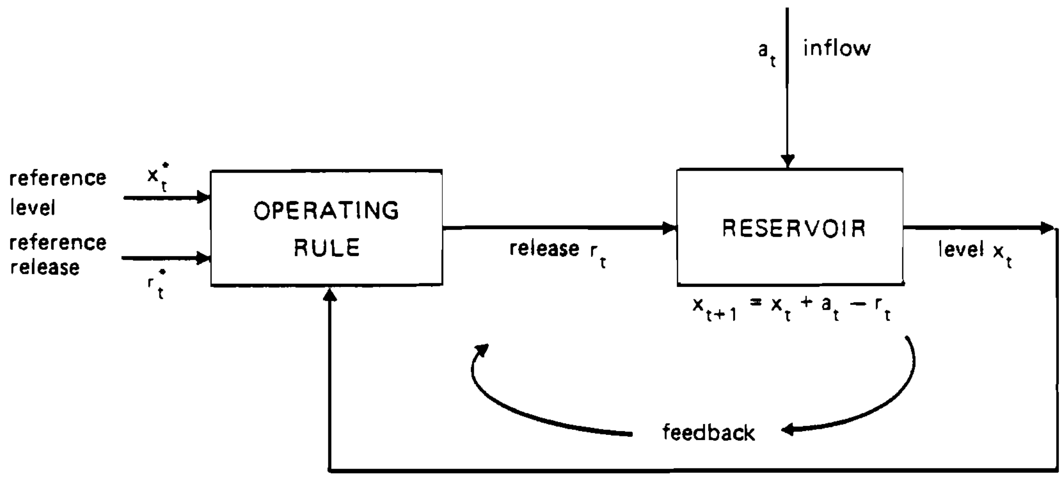

Figure 1. Feedback control scheme (operating rule).

usually known as <u>operating rule</u>

$$r_t = r(t, x_t) \tag{1}$$

The function $r(t, x_t)$ is periodic over the year with respect to t since all significant hydrologic and economic variables are generally well described by 1-year cyclostationary processes. Obviously, the operating rule also depends upon the reference levels and releases, which are nevertheless input data in the real-time decision making process.

A first natural extension of the above notion is to consider the possibility of making the release at any time t dependent upon the past k values of the storage. For example, the manager may often be sensitive to the derivative of the storage $[\simeq (x_t - x_{t-1})]$, which is an indirect measure of the current unknown inflow. In these cases the algebraic control law (1) is substituted by a more complex "dynamic" control law

$$r_t = r(t, x_t, x_{t-1}, \ldots, x_{t-k+1}) \tag{2}$$

Although Equations (1) and (2) often represent a satisfactory approximation of the decision-making process, one must recognize that in reality managers are much more subtle and use all the information available in real time on the reservoir catchment to take a decision, since this information can help in better evaluating the future availability of resource. The ways in which the information is processed and the decision is made can be interpreted again in terms of classical control schemes. Figure 2 shows a first case in which, in addition to the feedback channel of Figure 1, there is a <u>feedforward</u> channel bringing information (a vector $\underline{y}_t$) on the state of the catchment to the manager. Such information may be, for example, precipitation, snow cover, and depth of the water table in different points of the catchment. The controller is identified in this case by a control law of the type

$$r_t = r(t, x_t, \underline{y}_t) \tag{3}$$

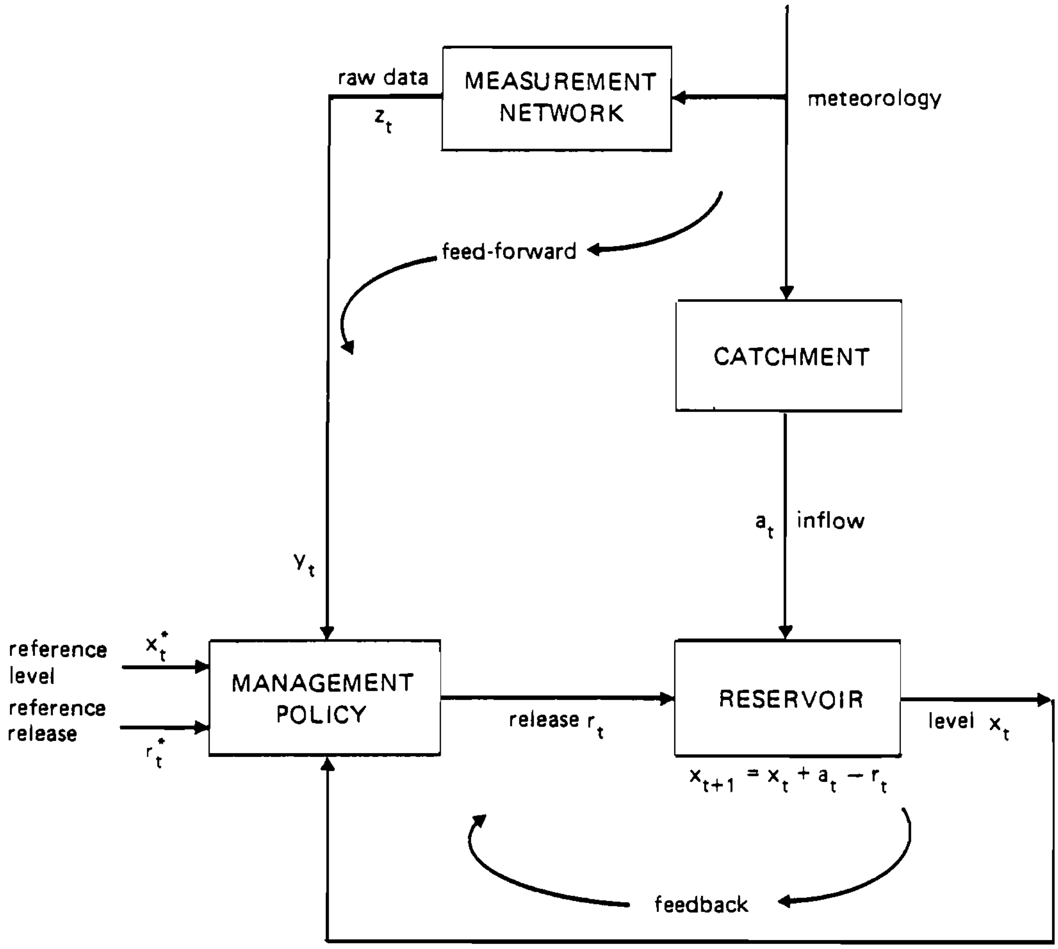

Figure 2. Feedback and feedforward control scheme (management policy) with direct use of information.

which will be called management policy from now on, in order to distinguish from the case of the operating rule (no dependence upon y_t). One could of course consider, as before, dynamic controllers, namely more complex computational procedures which determine r_t from present and past values of x_t and y_t. The main feature of these controllers, no matter if they are dynamic or not, is the fact that the decision making process is not decomposed into parts, but is represented by a unique "algorithm" working directly on the raw data z_t. For this reason such a situation ($y_t = z_t$) will be referred to in the following as direct use of information.

Figure 3, which is again a feedback plus feedforward control scheme, represents on the contrary the case in which the manager is supplied with an explicit forecast y_t of the inflow over a certain time range obtained by suitably elaborating the raw data $z_t, z_{t-1}, \dots$ (in practice these forecasts may be supplied by an agency or developed by the manager himself). Thus, the overall decision-making process is decomposed into two parts. A first part is devoted to forecast the inflows (or, equivalently, to estimate the state of the entire catchment), and a second part concentrates on the control aspects of the problem. This control block is again described by a management policy of the type (3), where obviously y_t represents a suitable forecast of the inflow. This control scheme (indirect use of information) has recently received great attention, thanks to the development of deterministic and stochastic models for inflow forecast.

The direct use of information (see Figure 2) entails a higher complexity of the management policy since in this case in Equation 3 y_t is a multidimensional vector, while the indirect use of information (see Figure 3) strongly reduces this complexity at the expenses of the introduction of an often heavy and costly forecasting procedure. It is important to notice that from a formal point of view the distinction between the two schemes may be rather fuzzy: the cascade (see Figure 3) of the inflow predictor (always constituted by a dynamic model) with the control block is in fact formally equivalent to a dynamic control law in which y_t is the vector of raw data ($y_t = z_t$). Thus, in order to avoid any possible confusion only

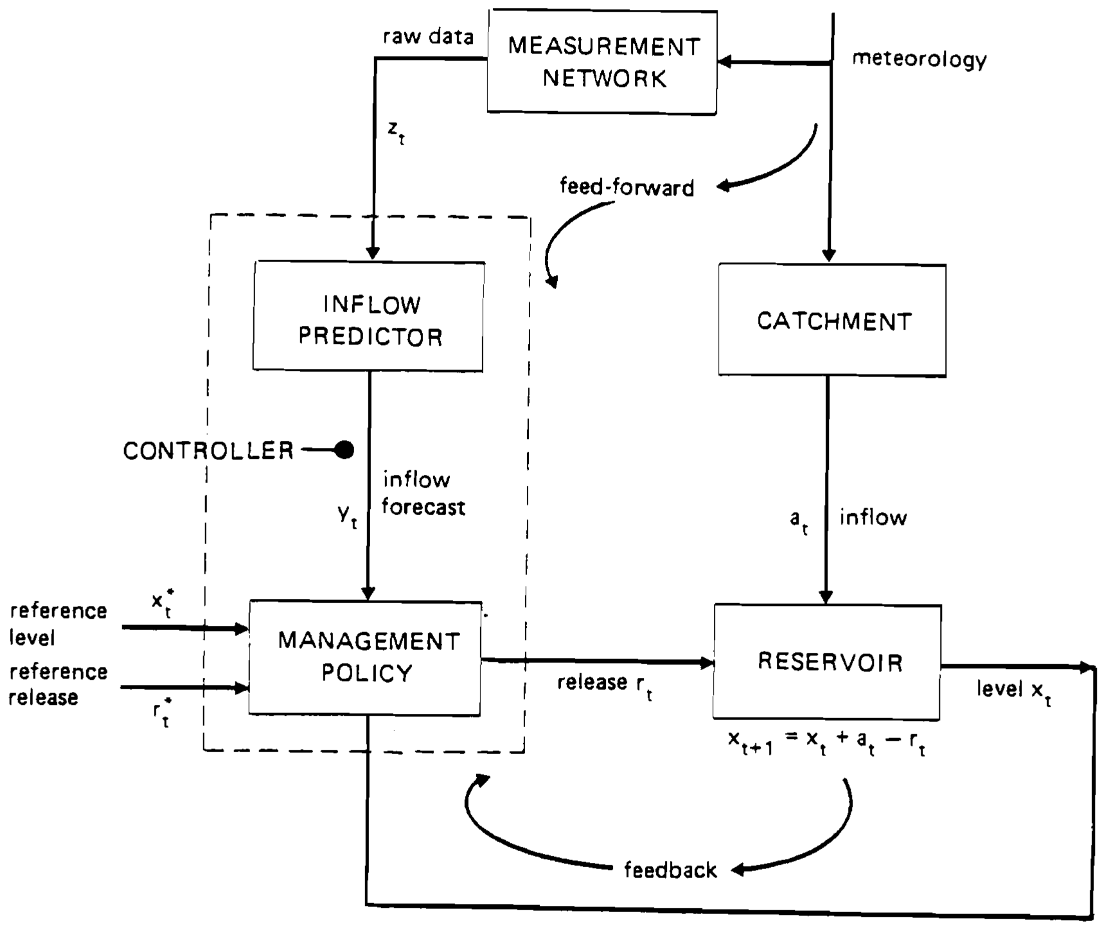

Figure 3. Feedback and feedforward control scheme (management policy) with indirect use of information (inflow predictor).

algebraic control laws (see Equations (1) and (3)) will be considered in the following, so that the two schemes of Figure 2 and 3 will indeed represent substantially different approaches to the reservoir control problem. In such a way it will be possible to clearly compare the two schemes and try to extract some first indicative conclusions about their performances and relative advantages.

3. A HEURISTIC APPROACH FOR THE BEST USE OF INFORMATION IN RESERVOIR MANAGEMENT

In this section a heuristic approach for the best use of real-time information in reservoir management is presented. The effort is focused on the possibility of bettering the operation of a given reservoir by making explicit use of the currently available information on the catchment. For this reason, we assume we know the operating rule

$$r_t = r(t, x_t)$$

which describes the decision making process when all variables y_t (raw data on the catchment or inflow forecasts) have their standard values y_t^*. Thus, the problem is reduced to find the best management policy for the control scheme of Figure 2, and the best inflow predictor and management policy for the control scheme of Figure 3. For both cases the proposed approach can be divided in the following three phases.

a. <u>Identification of the input y_t of the management policy</u>.
b. <u>Definition of acceptable management policies</u>.
c. <u>Determination of optimal management policies</u>.

The first phase is the most critical one (in particular in the case of direct use of information) and requires a strict cooperation between the analyst and the manager. It could be in principle very simple if any information reaching the manager is assumed to influence his decision. This may however generate dimensionality problems in the following phases (b) and (c) and must therefore be avoided whenever possible. In almost all practical cases, in fact, any kind of information (precipitation, temperature, snow cover, ...) is used only in particular periods of the year or only under special circumstances. Of course this must be suitably taken into account in order to reduce the dimensionality of the vector y_t. If the reservoir under study has been operated for a certain time, a way of selecting the components of y_t is the following. First, compare the historical releases with those that would have been obtained by systematically applying the operating rule $r(t, x_t)$, and then try to correlate the most relevant discrepancies with the deviations of some measured variable from its standard value. If the correlation is high, then this variable can be selected as a component of y_t. Examples of important components of the vector y_t are snow cover, rainfall, level of the underground aquifer, storage of upstream reservoirs, and flow-rate of upstream tributaries. In general, any variable which may indicate that a certain amount of water is already present in the catchment is a good candidate for the vector y_t, even if the time and magnitude of the inflows it will generate are not exactly known. In the case of indirect use of information (see Figure 3), the first phase of the procedure is essentially consituted by the development of an inflow predictor which, in turn, utilizes real-time hydrometeorological data like rainfall or snow cover.

Phase (b) requires to schematize by means of an appropriate set of acceptable management policies the dependence of the release r_t upon the extra information y_t. Technically, this must be done by fixing a function which depends upon a certain (possibly limited) number of unknown parameters to be optimized in the following phase (c). Some characteristics of this dependence are in general a priori known. First of all, whenever y_t is in standard conditions ($y_t = y_t^*$), the manager simply applies the operating rule $r(t, x_t)$. Furthermore, the release r_t suggested by the operating rule will be increased (or at least not decreased), whenever the value of y_t indicates abundance of water, and decreased in the opposite case (the rate of increase and decrease being in general different and unknown parameters). Moreover, as already pointed out, the dependence upon some of the components of y_t will be limited to precise periods of the year. Finally, the dependence upon y_t, should be such that the basic structure of the decision-making process remains as clear and simple as possible so that, working in close cooperation with the manager, the role played by the various pieces of information can be immediately understood and the suggested modifications can easily be accepted or suitably revised.

The last phase is the most technical one and is constituted by the traditional optimization procedure which determines the best values of the unknown parameters introduced in phase (b). The optimal solution is usually a unique management policy if the reservoir is single-purpose or a set of efficient (Pareto) management policies in the case of multipurpose reservoirs (see next section).

4. EXAMPLE OF APPLICATION

The approach outlined in the previous section has been applied to the case of Lake Como (see Figure 4) whose catchment of 4508 km^2 supplies water for hydropower production and irrigation of a large area in northern Italy. These, however, are not the only objectives of the management, since too frequent floods on the lake (in particular in Como town) must be avoided for obvious reasons. A preliminary study (Guariso et al. 1982) has shown that the above objectives may be quantified by the following physical indicators.

A = expected value of the annual volume of water deficit in agriculture with respect to nominal requirements [10^6 m^3].

E = expected value of the annual hydropower deficit with respect to production capacity [GWh].

F = expected number of days of flood per year in Como [days].

When deciding the value of the daily release, the manager is partially constrained by a license act issued by the Ministry of Public Works in 1942, before the beginning of the operation of the dam. In particular, the active storage of the lake is defined in that act. The operating rule implicitly used by the manager in the period 1946-1980 has been identified (see again Guariso et al. 1982) and has the form shown in Figure 5. Its basic features may be explained in the following way. In normal conditions the manager

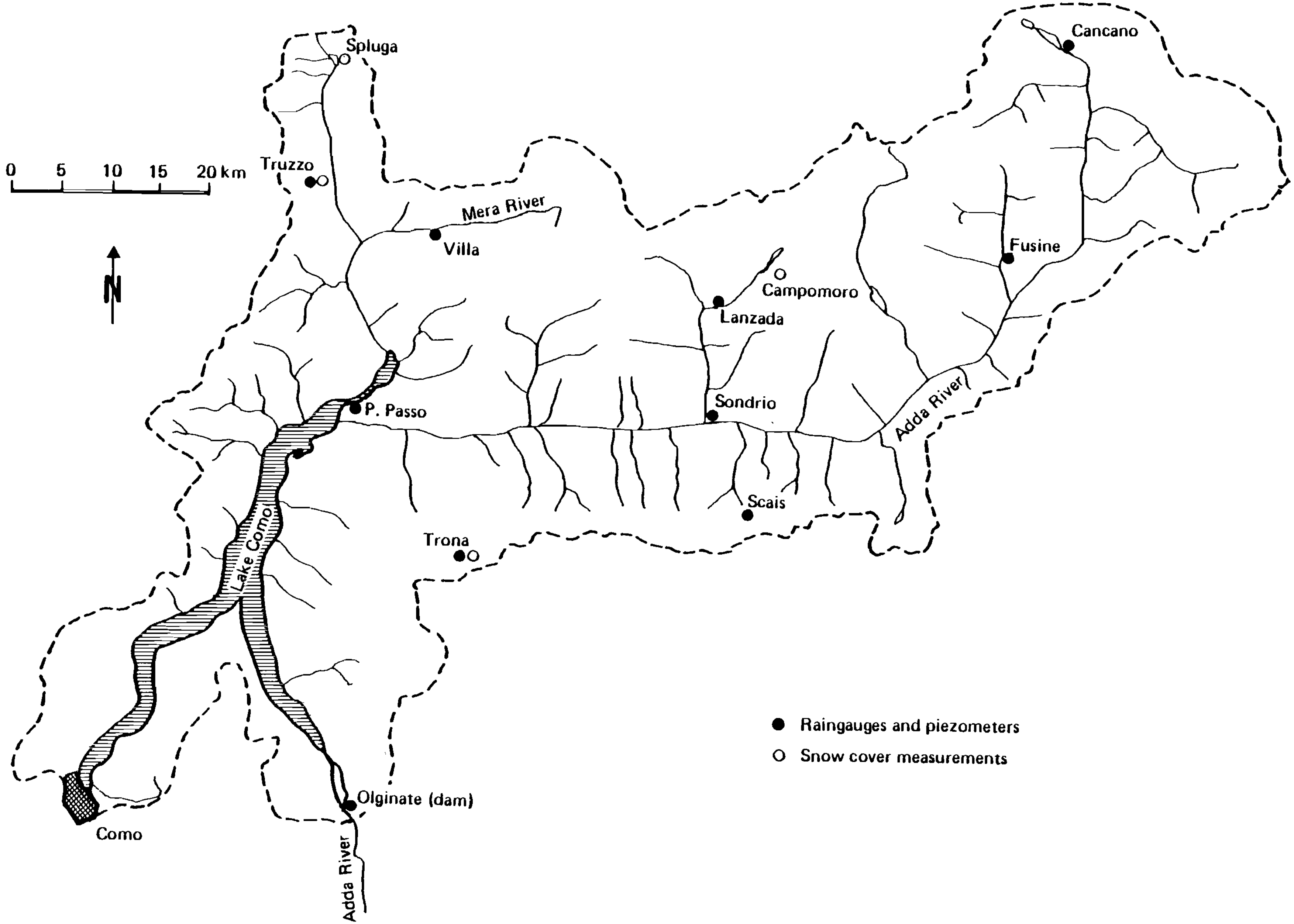

Figure 4. Lake Como catchment and measurement network.

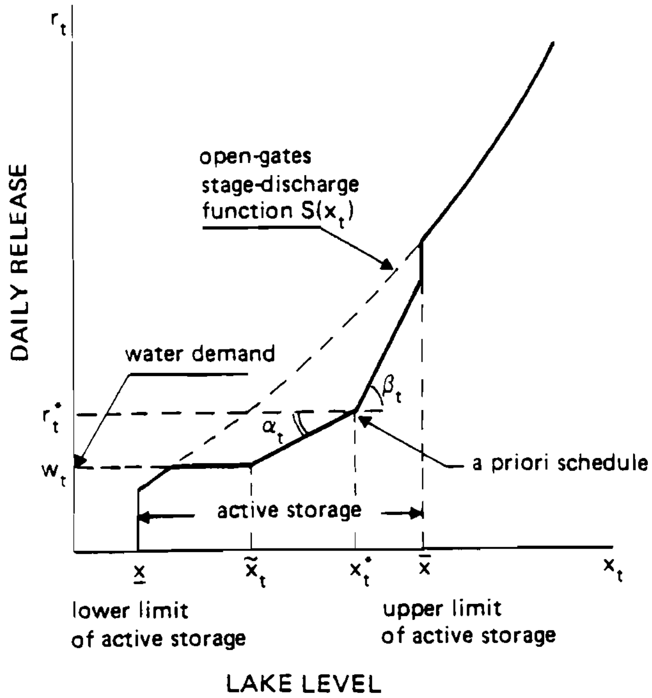

Figure 5. Lake Como operating rule.

follows the schedule (x_t^*, r_t^*), but whenever at the beginning of day t the lake level differs from x_t^* (rule curve), the manager varies the release by a quantity Δr_t which is dependent upon the surplus or lack of resource. More precisely, for relatively small deviations from the schedule ($\tilde{x}_t < x_t < \bar{x}$, see Figure 5) we have

$$\Delta r_t = \begin{cases} -\alpha_t(x_t^* - x_t) & \text{if} \quad \tilde{x}_t < x_t < x_t^* \\ \beta_t(x_t - x_t^*) & \text{if} \quad x_t^* < x_t < \bar{x} \end{cases} \tag{4}$$

If the level raises above the upper limit $\bar{x}$ of the active storage, the manager must follow the guidelines of the license act, which prescribe in this case to release as much water as possible from the regulation dam. In other words, when $x_t > \bar{x}$ the manager is obliged to release an amount of water equal to $S(x_t)$, where $S(\cdot)$ is the so called <u>stage-discharge function</u> of the lake. This function gives, for any value of the level x_t, the maximum amount of water which can be released in one day by keeping all the gates of the dam permanently open. On the contrary, if the level drops below the value $\tilde{x}_t$, where r_t equals the current water demand w_t of the downstream users, the release is maintained at this value w_t or to the maximum possible discharge $S(x_t)$. Finally, if $x_t = \underline{x}$ the release must be smaller than or equal to the current inflow, in order to avoid sanitary problems and difficulties for navigation. For particular values (α_t^*, β_t^*) of the parameters appearing in Equation 4, the operating rule interprets in a satisfactory way the historical data. Moreover, a set of efficient operating rules was obtained by solving the following stochastic multiobjective optimization problem

$$\min_{\{a,b\}} \quad [A \quad E \quad F]$$

subject to

$$x_{t+1} = x_t + a_t - r(t, x_t, a, b)$$

where the inflow a_t is a one-year cyclostationary-stochastic process and $r(t, x_t, a, b)$ is a family of operating rules of the kind shown in Figure 5 with

$$\alpha_t = a\,\alpha_t^* \quad , \qquad \beta_t = b\,\beta_t^* \quad .$$

The solution of this mathematical programming problem specifies the values of the two unknown parameters a and b, and of the three objectives A, E, and F. All the efficient operating rules obtained by solving the above mathematical programming problem are structurally similar to the one used by the manager in the past. In fact, the constraints $\alpha_t = a\,\alpha_t^*$, $\beta_t = b\,\beta_t^*$, guarantee that the relative seasonal variations of α_t^* and β_t^* (which obviously represent the sensitivity of the manager to floods and droughts) are preserved. The values of the objectives A and F have been estimated by simulating the period 1965-1979 and by keeping E fixed at its historical value. The set of efficient solutions is shown in Figure 6 where point H represents the historical values of the objectives, and point U their absolute (independent and hence infeasible) minima. Comparing, for example, point P on the Pareto set with point H it appears that both agricultural deficits and floods in Como can be reduced to about half of their historical values.

The approach outlined in the preceding section has been applied with reference to the operating rule corresponding to point P in Figure 6, which makes the best use of the information on the reservoir storage. The choice of such an efficient point is obviously necessary if one likes to evaluate in a correct way the improvement due to the surplus of information (y_t).

4.1 Direct Use of Information

(a) <u>Identification of y_t</u>

The manager has indicated that the following variables are particularly important for the daily operation of the lake.

1. y_t^1 = snow cover in the period February-June
2. y_t^2 = depth of the aquifer all the year round
3. y_t^3 = rainfall during the two preceding days in the period March-November

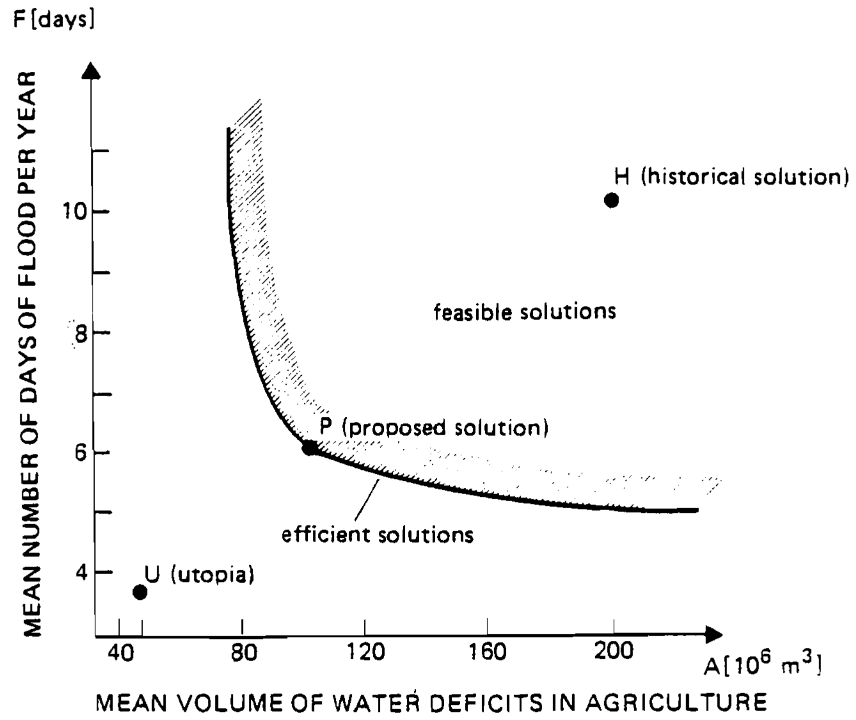

Figure 6. Performance of the system with no use of feedforward (operating rule): feasible and efficient solutions, historical value of the objectives (point H), and absolute minimum value of the objectives (point U).

The analysis of the most significant discrepancies between the historical releases and those that would have been obtained by using the operating rule relative to point H of Figure 6 confirmed this assumption, and allowed to exclude that the storages of the upstream reservoirs had any relevance for the operation of the lake (the variations of these storages from year to year are indeed only minor and strictly related to snow cover).

(b) Acceptable management policies

From the above analysis it appeared that the effect of the three variables $y_t^i (i = 1, 2, 3)$ mentioned above was mainly to induce releases similar to those that would have been obtained using an operating rule with a different schedule (x_t^*, r_t^*). It has thus been assumed that the management policy $r(t, x_t, y_t)$ could be formally obtained from the operating rule relative to point P in Figure 6 by making the reference level x_t^* and release r_t^* dependent upon y_t. More precisely, the variation $\delta^i x_t^*$ and/or $\delta^i r_t^*$ of the reference values x_t^* and r_t^* induced by the i-th component of y_t were assumed to be proportional to the difference between the actual value y_t^i and a prespecified or unknown standard value $\bar{y}_t^i$. In particular, whenever y_t^i indicated an increase of availability of water, only the level x_t^* was decreased, meaning that less storage was required in the lake if more resource is known to be available upstream. On the contrary, if y_t^i indicated that less water than usual was present upstream, only the release r_t^* was lowered in order to store more water than in standard conditions and still satisfy the demand during the following dry season. In conclusion, the management policies that were considered to be acceptable are again shaped as the operating rule in Figure 5, with the following variations to the schedule (x_t^*, r_t^*)

$$\delta^i x_t^* = - \gamma_i (y_t^i - \bar{y}_t^i) \quad , \qquad \delta^i r_t^* = 0 \qquad \text{if} \quad y_t^i > \bar{y}_t^i \qquad (5a)$$

$$\delta^i x_t^* = 0 \quad , \qquad \delta^i r_t^* = - \varepsilon_i (\bar{y}_t^i - y_t^i) \qquad \text{if} \quad y_t^i < \bar{y}_t^i \qquad (5b)$$

so that, if the effects of all the three components of y_t are considered together, the overall corrections δx_t^* and δr_t^* of x_t^* and r_t^* are

$$\delta x_t^* = \Sigma_{1i}^{3} \delta^i x_t^* \quad , \qquad \delta r_t^* = \Sigma_{1i}^{3} \delta^i r_t^*$$

Average spatial values of snow cover, depth of the aquifer, and rainfall were used to compute each day the vector y_t (see Figure 4 where the measurement network is indicated). The standard values $\bar{y}_t^i$ for snow cover and aquifer depth $(i = 1, 2)$ were fixed a priori for each day t of the year as the smoothed temporal mean over the period 1965-1979, while for rainfall $(i = 3)$ the standard value was assumed to be an unknown parameter constant during the year $(\bar{y}_t^3 = \bar{y}^3)$. Furthermore, since the information on the rainfall in the last two days is obviously of interest only for avoiding floods, the parameter ε_3 in Equation (5b) was assumed to be zero, so that no correction to the reference schedule could be applied for $i = 3$ unless it rains intensively on the whole catchment. When using the complete vector y_t, the management policy is thus defined as a function

$$r_t = r(t, x_t, y_t, p)$$

where p is the following unknown vector of parameters

$$p = | \gamma_1, \varepsilon_1; \quad \gamma_2, \varepsilon_2; \quad \gamma_3, \bar{y}^3 |$$

Consistently, if only one component of y_t is used, the dimension of p reduces to two.

(c) Optimal management policies

Either using one or more variables y_t^i, the determination of the optimal value p^o of the vector of parameters can simply be accomplished by solving the following stochastic multiobjective problem

$$\min_{\{p\}} \quad [\Lambda \quad E \quad F] \tag{6}$$

subject to

$$x_{t+1} = x_t + a_t - r(t, x_t, y_t, p) \tag{7}$$

where the management policy $r(t, x_t, y_t, p)$ belongs to the class defined above. The optimal solution of this problem is obviously constituted by a set of efficient (Pareto) policies each one corresponding to a different p^o. This set of efficient policies has been found by estimating the value of the objectives through repetitive simulations of the period 1965-1979 (an adaptive random search program was used to suitably vary the value of p at each step). The final results of the optimization are presented and discussed in Section 5.

4.2 Indirect Use of Information

(a) Identification of y_t

As already pointed out in the case of indirect use of information (see Figure 3) the variable y_t entering the controller is a real-time forecast $\hat{a}_{t+\tau}$ of the total inflow over the next τ days based on the knowledge of hydrometeorological data. For this reason, a number of inflow predictors have been developed and tested following the general suggestions and conclusions recently outlined by O'Connell and Clark (1981) and Shaarawi (1982).

The first predictor was a stochastic autoregressive moving average model using rainfall data as exogenous inputs (ARMAX) originally developed by Bolzern et al. (1980, 1981). The structure of the model is the following

$$\hat{a}_{t+1} = \begin{cases} \Sigma_{0j}^{p} \; c'_j a_{t-j} + \Sigma_{0k}^{q} \; d'_k \; u_{t-k} + \Sigma_{0i}^{r} e'_i \, \varepsilon_{t-i} & \text{if} \quad \Sigma_{0i}^{s} \; u_{t-1} < K \\ \Sigma_{0j}^{p} \; c''_i a_{t-j} + \Sigma_{0k}^{q} \; d''_k \; u_{t-k} + \Sigma_{0i}^{r} e''_i \varepsilon_{t-1} & \text{if} \quad \Sigma_{0i}^{s} \; u_{t-1} \geq K \end{cases}$$

which means that the value of the inflow at time t + 1 may be represented by a linear combination of past values of the same inflow, of terms of past rainfall u_{t-k} and of past "errors" ε_{t-i}.

The coefficients c, d, and e of the model switch between two different values (c', d', e') and (c", d", e") to partially reflect current conditions of the soil in the catchment: "dry" if total rainfall during the last s days is below a given threshold K, "wet" otherwise). The values of the parameters were estimated by a recursive least square procedure outlined by Panuska (1969), while the model order p, q, r as well as the values of s and K were defined by using Akaike's method and cumulative periodogram test. The final performance of the model was highly satisfactory for one day ahead prediction (see first row of Table 1). An analysis of the residuals ε_{t+1} proved, in fact, that they have zero mean, and the ratio between their standard deviation and the standard deviation of the inflows is 0.48, while the correlation between real values and predicted values of the inflows is 0.87. Even in the case of high flowrates ($a_t \geq 350\, m^3/sec$) the ratio $\sigma_\varepsilon/\sigma$ is still equal to 0.49, and becomes 0.52 when analyzing only periods of sudden flow increase ($a_t - a_{t-1} > 100\, m^3/sec$) which usually characterize the beginning of a flood. Since the time lag between rainfall and corresponding water inflow is definitely less than 24 hours (particularly during floods) the performance of this kind of predictor worsens rapidly when increasing the length of prediction above one day.

The second predictor was a linear recursive model to forecast the total inflow of the following three days on the basis of the separate values of the inflow in the three preceeding days. The performance of this predictor was obviously worse than that of the one day ahead predictor. Nevertheless, the accuracy of forecast can be partially improved by using the one day ahead prediction as a corrective term. The final overall performance, again measured as noise to signal ratio $\sigma_\varepsilon/\sigma$, was 0.62 with a slightly higher value (0.67) at the beginning of the floods (second row of Table 1).

The third kind of predictor tested was a simple AR(1) predictor for the 7-days ahead mean inflow. It is obvious that the pattern of inflows over such a 7 days period has a relevant

Table 1. Performance of the inflow predictors used in the study.

	overall		beginning of floods	
Time lag τ	$\sigma_\varepsilon/\sigma$	ρ	$\sigma_\varepsilon/\sigma$	ρ
1 day	0.48	0.87	0.52	0.86
3 days	0.62	0.80	0.67	0.76
7 days	0.75	0.69	0.86	0.61

importance, but a forecast of the mean value seemed the only reasonable request over such a time span and, as it will be proved later, it can still be useful for the manager. The performances of this model are clearly poorer than those of the preceding models, giving a correlation between forecast and real values of 0.69 and a ratio $\sigma_{\varepsilon}/\sigma$ equal to 0.75 (see last row of Table 1).

Finally, a conceptual snow-melt, rainfall-runoff model was developed and tested. The catchment was divided into five layers of different elevations from the lower level (200 m a.s.l.) to the highest mountain peak (4050 m a.s.l.). Each layer was modelled with two compartments: one for snowmelt, driven by snowfall and air temperature, and one for rainfall - runoff driven by the precipitation in the form of rain. The physical structure of the catchment enters the model through a certain number of mass-balance equations and parameters. Some of these parameters, like the area caught by upstream hydroelectric reservoirs, could be directly measured, while others, like the precipitation-elevation correction, were estimated on the basis of historical data. This model proved to be very satisfactory to generate a sound synthetic series of data and to interpret the sensitivity of the snow-melt, rainfall-runoff relationships to structural variations of the characteristics of the river basin (deforestation, urbanization, development of upstream reservoirs, ...). Unfortunately, it substantially failed when used to predict in real time the inflows into the lake. Indeed, the performance of the corresponding predictor, even for one day ahead prediction, was slightly inferior to that of the ARMAX model, in particular during flood episodes. For this reason, such a predictor has not been used in the following phases.

(b) Acceptable management policies

The second phase of the procedure requires the definition of the acceptable management policies which, in this case, are simply relationships between the inflow forecast $\hat{a}_{t+\tau}$, and the release r_t. For consistency, the same relationships described in the case of direct use of information have been used, so that the schedule (x_t^*, r_t^*) was perturbed in the following way

$$\delta x_t^* = -\gamma(\hat{a}_{t+\tau} - \bar{a}_{t+\tau}) \quad ; \quad \delta r_t^* = 0 \qquad \text{if} \quad \hat{a}_{t+\tau} > \bar{a}_{t+\tau}$$

$$\delta x_t^* = 0 \quad ; \quad \delta r_t^* = -\varepsilon(\bar{a}_{t+\tau} - \hat{a}_{t+\tau}) \qquad \text{if} \quad \hat{a}_{t+\tau} < \bar{a}_{t+\tau}$$

where $\hat{a}_{t+\tau}$ and $\bar{a}_{t+\tau}$ represent, respectively, the forecast available at time t, and a prespecified standard value of the total inflow in the period $[t, t+\tau]$.

(c) Optimal management policies

Once more the determination of the optimal value of the two-dimensional vector $p = |\gamma\ \varepsilon|$ of unknown parameters can be accomplished by solving the multiobjective program (6-7), thus finding a set of efficient management policies for each kind of predictor used. The results of this optimization are presented in the next section.

5. ANALYSIS OF THE RESULTS

The direct use of hydrometeorological data led to the results shown in Figure 7 in the plane (A, F) for constant hydropower deficit (E = historical value). The three curves denoted by [1], [2], and [3] represent the efficient solutions which can be reached considering only one variable (snow cover, aquifer depth, rainfall) at a time and solving problem (6-7) with respect to the unknown parameters $(\gamma_1, \varepsilon_1)$, $(\gamma_2, \varepsilon_2)$, and $(\gamma_3, \bar{y}^3)$. These Pareto sets show the improvements one can obtain with respect to point P by using only one extra variable. In each case the improvement is not irrelevant, particularly if compared with point U representing the utopic situation in which the agricultural deficit A and the number of days of flood F are at their respective absolute minimum values. The use of information on snow cover may, for instance, decrease

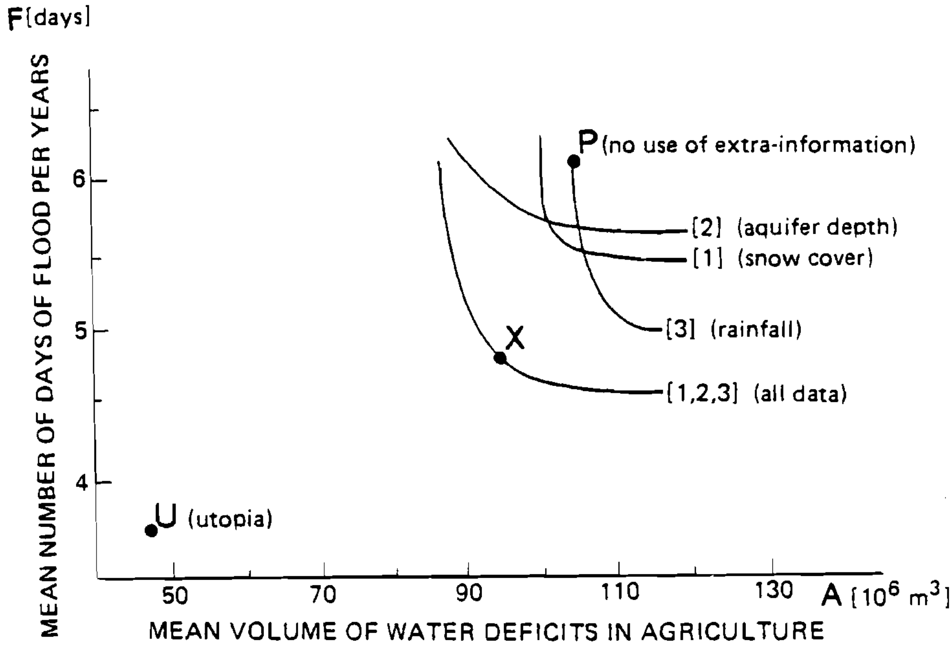

Figure 7. Efficient solutions with direct use of information.

agricultural deficits of 8.4% and floods of 17.7% of the maximum possible improvement (distance between points P and U). Similarly, the information on the underground aquifer may improve contemporarily floods and agricultural deficits by about 13%. On the contrary, the information on rainfall produces positive effects only on floods, but may reach 41% with only a 8.7% increase in agricultural deficit. The combined use of the three variables produces the Pareto set denoted by [1, 2, 3] in Figure 7, which is very close to the curve that can be obtained by a simple vectorial sum of the effects of the three variables used separately. This is obviously due to the fact that the three considered components of y_t are largely independent from each other. It can be concluded that the direct use of information considerably improves the management of the lake. For example, point X on the [1, 2, 3] efficient set, represents a 20% reduction of agricultural deficits and a 55% reduction of floods with respect to the maximum possible improvements.

The results obtained using inflow predictors are shown in Figure 8 where curves [1], [2], and [3] represent the performances of the management policy using the one, three, and seven days ahead predictors illustrated in the previous section, while curves $[1]^0$, $[2]^0$, and $[3]^0$ represent what would be achieved if such predictors were perfect (forecast equal to actual inflow). It appears that perfect forecasts over longer time intervals are more useful for the manager (curves $[1]^0$, $[2]^0$, and $[3]^0$ are ordered from point P to the utopia point U). Nevertheless, the progressive loss of precision of the real predictors has a very heavy effect on the final results: for example, curve [3] is completely dominated by the two other curves. Of course, one could also use the three predictors at the same time, as done in the case of direct use of information. Unfortunately, in this case the corresponding Pareto set [1, 2, 3] is only slightly better than [2], so that the use of such a complex decision making process is really not justified. The reason for this is that the forecasts provided by the three predictors are highly correlated one to each other, since all models make use in different ways of the same information (recorded values of precipitation and inflow).

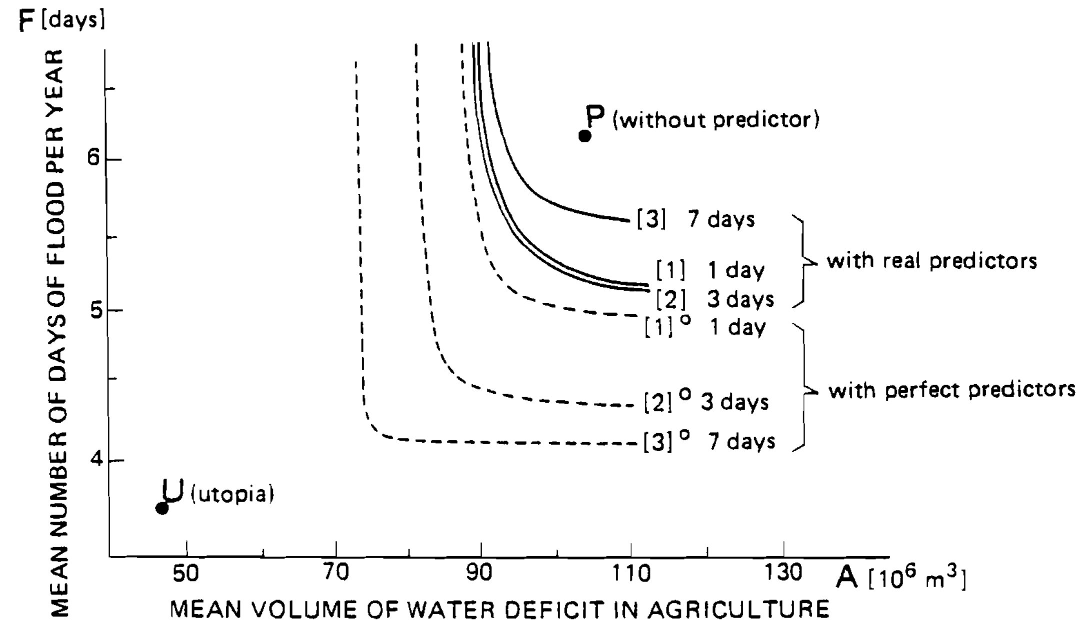

Figure 8. Efficient solutions with indirect use of information.

A comparison of Figures 7 and 8 shows that the direct use of information gives better results. Curve [1, 2, 3] in Figure 7, in fact, roughly corresponds to the curve that would be obtained with a perfect two-days ahead forecast, something definitely impossible on a river basin such as the one considered in this study. An efficient management policy based on the direct use of information was thus finally selected by the manager of Lake Como. This management policy has been programmed on a microcomputer (based on a Z80 microprocessor) which is presently used every day for the management of the lake. The computer recalls to the manager how the optimal release is obtained, and shows separately the effects due to all different sources of information, thus giving to the manager the chance to become more and more aware of the real value of the different pieces of information he has.

6. CONCLUDING REMARKS

This paper has confirmed that considerable benefits can be achieved when operating a multipurpose reservoir by using real time information on the catchment. The heuristic procedure proposed in the paper allows a comparison of the relative advantages of different kinds of information as well as on the extension of the measurement network.

The case study examined in the paper seems to suggest that the direct use of raw hydrometeorological data has some advantage with respect to the use of inflow forecast. This result may be partly related with the fact that, when directly using the information, each significant hydrometeorological data has an immediate effect on the reservoir release. On the contrary, the use of inflow predictors introduces a filtering effect on the sudden variations of the data. Moreover, the use of predictors focuses the effort of the analyst on model calibration under the dogma that a better prediction will give rise to a better management. But unfortunately this is not always the case, since the minimization of the "overall" prediction error, which is behind the majority of the algorithms for model calibration, is in general a criterion which has only little to do with the real objectives of the management. Indeed, very often during the course of the year the manager is almost not interested in the inflow forecast since the kind of variations of the inflow that might occur cannot really influence the performance of the management. On the contrary, errors or delays in prediction may have in particular circumstances catastrophic effects on the objectives. In other words, it is very important that the forecast is good but only at the right time.

The conclusion of this study is not in line with the enthusiasm for inflow predictors certainly detectable in the recent literature. In fact, the results obtained seem to indicate that the direct use of information that reservoir managers have indeed often experienced, constitutes in practice, if not in principle, an approach that will be difficult to overcome, even with sophisticated inflow predictors. This means, in other words, that a revision of the philosophy of the calibration of inflow forecasting models is probably necessary if these models have really to serve as useful tools for reservoir management.

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