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THE USE OF PROBABILISTIC CONSTRAINTS IN RESERVOIR OPERATION POLICIES WITH SAMPLING STOCHASTIC DYNAMIC PROGRAMMING

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The role of mathematical simulation and optimization models in hydropower planning at Pacific Gas and Electric Company is discussed, and some of the models are described. Applications of sampling stochastic dynamic programing to develop reservoir release rules for the simulation models are presented. Probabilistic constraints on the minimum reservoir storage value are explicitly considered. The models for PG&E's North Fork Feather River hydroelectric system are used as an example.

Introduction

Electric generation planning is a complex process involving forecasts of loads and projections of available resources. Planners in California, where hydroelectric facilities constitute a significant portion of a diverse resource mix, face additional challenges. Accurate modeling and dispatching of hydropower operation requires consideration of not only system constraints and the scheduling of other resources, but also streamflow variability and economics. The variability of hydrologic conditions creates uncertainty in the available hydroelectric capacity and energy.

To help planners deal with this uncertainty, many mathematical simulation models have been developed (Yeh, 1985), operating on either historical or synthetic streamflow data. The seasonal variation of streamflows makes the scheduling of hydroelectric generation another challenge. Optimization models have been developed to solve this scheduling problem using deterministic nonlinear programming (Ikura and Gross, 1984) and stochastic dynamic programming (Loucks et al., 1981; Stedinger et al., 1984).

This paper describes part of the hydropower planning process at Pacific Gas and Electric Company (PG&E). The use of water and power (simulation) models and a new model employing sampling stochastic dynamic programming (SSDP) are discussed. Two applications of the planning models for PG&E's North Fork Feather River hydroelectric system are presented.

Hydro Planning at PG&E

Figure 1 shows the typical hydropower planning process at PG&E and the flow of data between various mathematical models. The water and power models are designed to simulate the operation and dispatch of PG&E's hydroelectric facilities. They are used to generate a data base of long-term average annual generation and dependable capacity for each powerhouse in the PG&E system. This data base is used as part of the input to the electric production simulation models, such as PROMOD and UPLAN, which use this information along with data on nonhydro resources to simulate power production for a particular load forecast and outage

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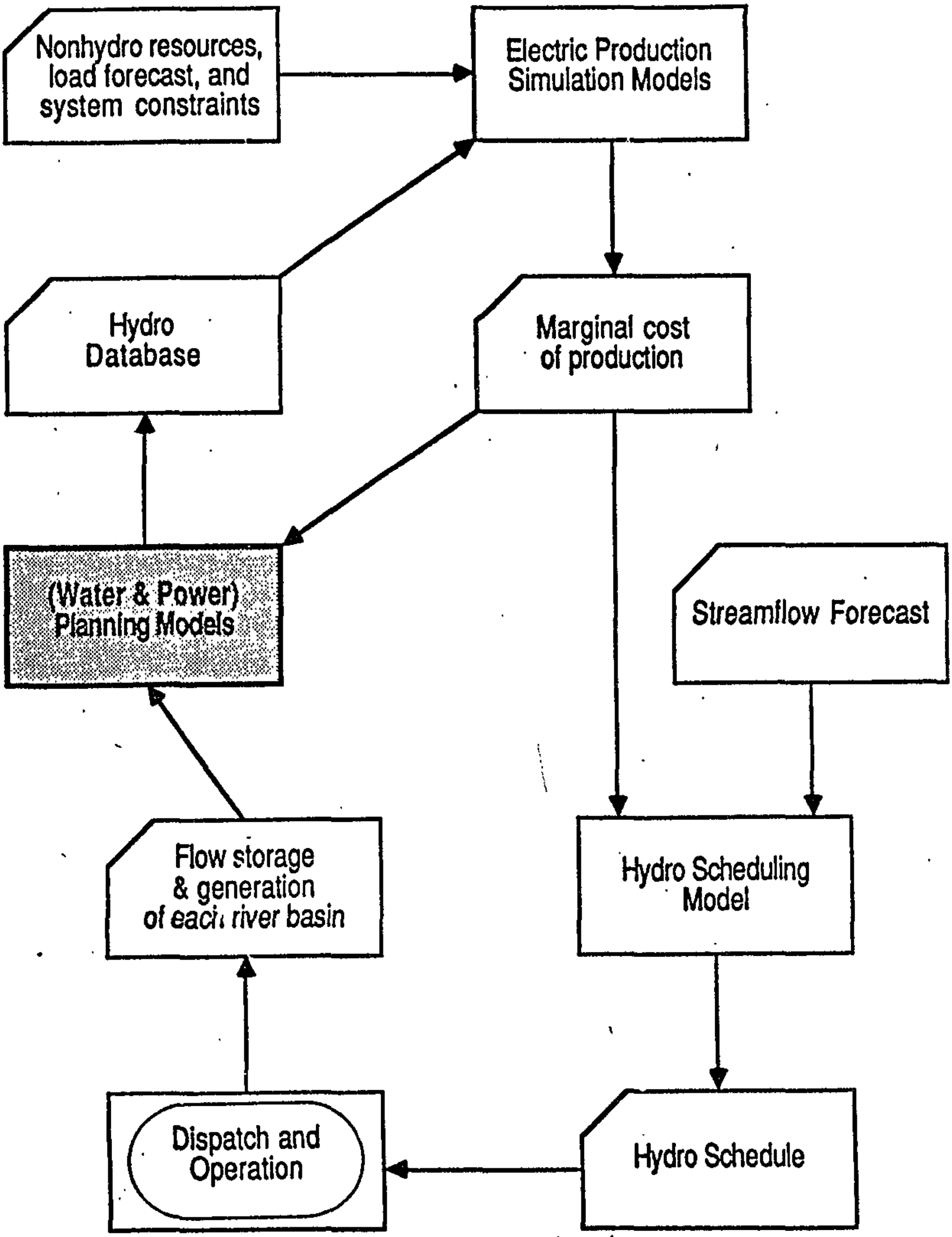

Figure 1. Typical Hydropower Planning Process

schedule within system constraints. One of the outputs of the production simulation model is the marginal cost of electric generation. These marginal costs are used by both the simulation models and the hydro scheduling model. The schedules developed by the latter are used to guide the operation and dispatch of powerhouses.

In this planning process, each stage of model runs takes one to three months. Any update of the existing conditions or significant changes in the assumptions--such as oil prices, load forecasts and new resources--requires a lengthy process before its effects can be included in the data base. This update process is a substantial, ongoing effort of the planning department.

Water and Power Models

Over many years, PG&E has developed an extensive library of water and power models (about 100 programs) for 15 watersheds in northern and central California. These programs simulate the operation of each river basin's hydroelectric facilities based on historical streamflow data and the physical characteristics of the reservoirs and powerhouses. These models are highly detailed to capture regulatory, operational, contractual, and physical constraints.

One major feature of the water and power models is the ability to simulate any possible future developments in each watershed. As planning tools, the programs contain not only the existing powerhouses and reservoirs, but also various system additions being contemplated. Modification of the water and power models to include new development plans is an ongoing effort of the planning department, since regulations and business opportunities are ever-changing.

Another important feature of the water and power models is the flexibility of following different generation strategies. Because hydroelectric generation is seasonal, the models are designed to be controlled by reservoir rule curves, i.e. target storage levels for the end of each month. By varying the rule curves, planners can simulate different generation strategies.

For most planning purposes, it is important to have rule curves that maximize annual power generation or annual benefits. Traditionally, the rule curves were developed through a difficult trial-and-error process. An optimization model could develop the rules instead, in a relatively automated manner.

Sampling Stochastic Dynamic Programming

Kelman et al. (1988) developed a methodology based on sampling stochastic dynamic programming (SSDP) for optimizing the reservoir operation rule curves. In this method, the objective is to maximize expected energy production or its benefit over a 12-month horizon. The decision variable is the release from the reservoir in each stage (month) while the state variables are the storage and hydrologic forecast. The method assumes implicitly that the future streamflow sequence in the basin, from next month to the end of the horizon, will be exactly equal to a streamflow scenario that has actually occurred in the past. A large number M of streamflow scenarios is used to capture the variability of the streamflow process. When the release decision is being made at stage t, the likelihood of sampling any of the streamflow scenarios, from stage t+1 onward, depends on the hydrologic forecast state variable.

At each stage t and state, a release decision is made by balancing the expected immediate (in stage t) benefit against the expected future benefit:

$$\max_{R_t^*} \left\{ \sum_{i=1}^{M} P_t(i|l) \left[B_t(R_t, i, k, S_{t+1}) + a \sum_{v=1}^{L} PX_t(v|l,i)\, f_{t+1}(S_{t+1}, v, i) \right] \right\} \quad (1)$$

where
i = the streamflow scenario index;
v = the hydrologic forecast index;
S_t = the reservoir's storage at stage t, discretized into K values (k=1,...,K) with $S_t(1)=S_{min}$ and $S_t(K)=S_{max}$;
X_t = the hydrologic forecast at stage t, discretized into L values (l=1, ..., L)
$P_t(i|l)$ = the probability of scenario i at stage t, given forecast $X_t(l)$;
R_t^* = the optimum target release from the reservoir;
R_t = the actual release from the reservoir in month t;
B_t = the immediate benefit in month t of release R_t;
$PX_t(v|l,i)$ = the transition probability from forecast $X_t(l)$ to forecast $X_{t+1}(v)$ in scenario i;
f_{t+1} = the future benefit from month t+1 to T, the end of the horizon;
a = the monthly financial discount rate.

Figure 2 shows the tradeoff between the immediate and future benefits and the selection of the optimal target release. The actual release is further constrained by the water balance in the reservoir, with the storage after release between S_{max} and S_{min}:

$$R_t = \text{Min}\,[S_t+Q_t-S_{min}-E_t(S_t,S_{min}), \text{Max}[S_t+Q_t-S_{max}-E_t(S_t,S_{max}), R_t^*]] \quad (2)$$

where
Q_t = inflow;
E_t = evaporation and leakage loss of the reservoir.

After the optimum target release R_t^* is determined, the future benefit for each streamflow scenario is calculated as:

$$f_t(S_t,l,i) = B_t(R_t,i,k,S_{t+1}) + a \sum_{v=1}^{L} [PX_t(v|l,i)\, f_{t+1}(S_{t+1},v,i)] \quad (3)$$

With no forecast state variable, equation (3) simplifies to:

$$f_t(S_t,i) = B_t(R_t,i,k,S_{t+1}) + a\, f_{t+1}(S_{t+1},i) \quad (4)$$

The SSDP algorithm is implemented in a FORTRAN program that essentially consists of several nested DO loops. For each month and discrete storage state value, discrete target release values are considered. The end-of-month storage level and expected immediate, future, and total benefits are calculated over all the streamflow

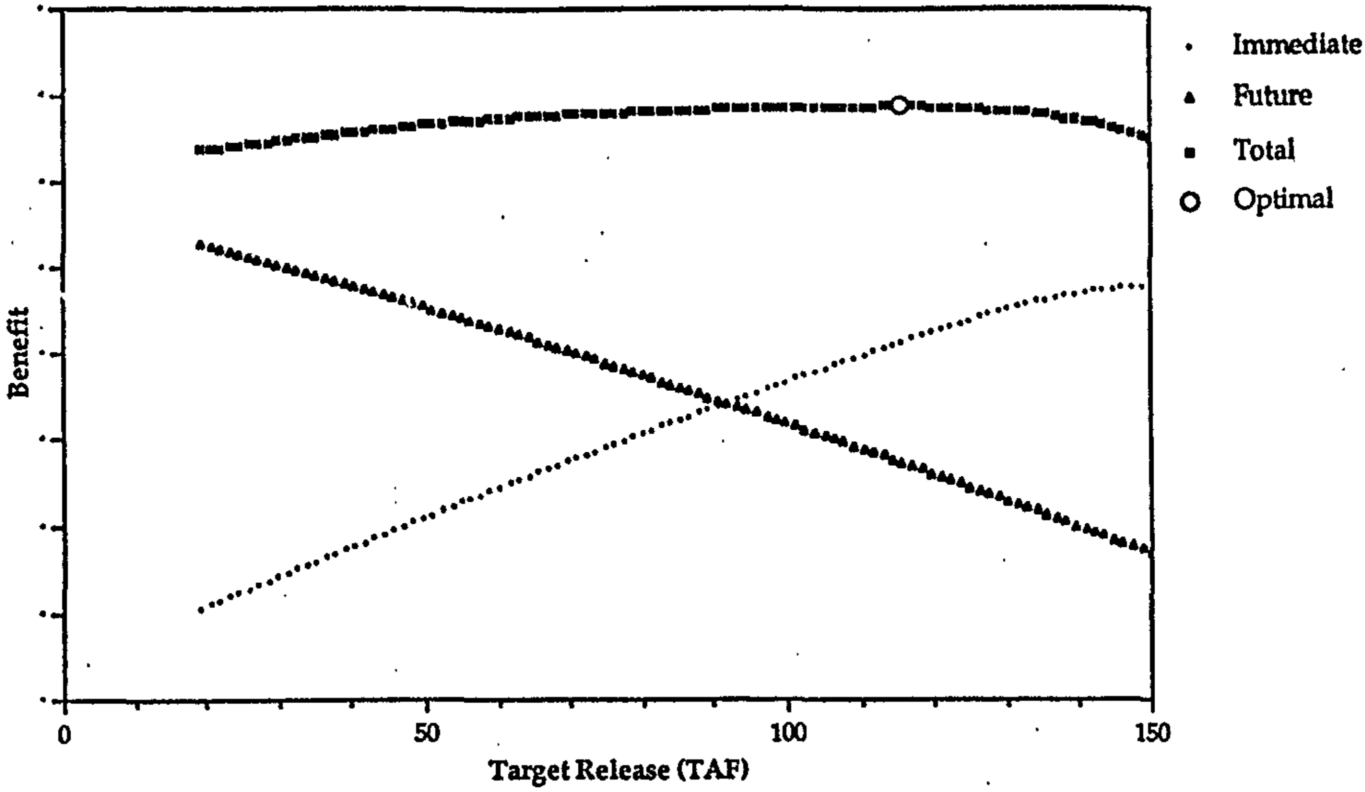

Figure 2. SSDP Objective Function

scenarios until the largest total benefit is found.

Applications of the Models

Two applications of the SSDP model in the rule curve development for water and power programs will be discussed. The planning models for PG&E's North Fork Feather River (NFFR) hydroelectric system in Northern California are used to demonstrate the approach. No actual operations of the system are simulated.

The Feather River system consists of one major reservoir and six downstream powerhouses, totaling about 660 megawatts of installed capacity. See Figure 3 of the NFFR watershed. A major uncontrolled downstream tributary affects three of the powerhouses. The rule curves in the water and power model must be flexible enough to accommodate the uncontrolled spring runoff and to meet typical summer and autumn energy requirements. There are also several downstream water supply requirements and water rights issues associated with the river system which must be considered in developing the rule curves.

A. Impact of Minimum Storage on the Rule Curve

The SSDP model was used to develop the optimum rule curves for the water and power model using various minimum storage values. The different sets of target releases (from which the target storage levels can be derived) from the SSDP model were then applied in the water and power model to determine the average annual generation benefits of the hydroelectric facilities. The results are shown in Figure 4.

Also noted in Figure 4 is the point corresponding to the original rule curve used in the water and power model. This rule curve was developed by trial and error. Although the difference in annual benefits is not substantial, the SSDP model was able to develop a better rule in much less time.

This study indicates that lower minimum storage levels yield larger benefits (annual generation). The rule curve developed for low minimum storage is very aggressive in varying the simulated reservoir levels. This type of operation is thus favored on an economic basis.

B. Probabilistic Constraints

Operation of hydroelectric systems, however, is not dictated by economics alone. Environmental impacts, aesthetics, safety considerations, and recreation also must be considered. Since reservoirs are popular sites for summer water sports, drastic water level variations could affect recreation. The application of the planning models to measure the effect of this constraint will be discussed.

In solving the objective function (1), a compromise between energy production and the constraint on reservoir level could be reached by allowing the reservoir to drop below a certain level S^*, in some month t, given any S_{t-1}, during a limited number of years. The following probabilistic constraint could be enforced whenever possible to model this compromise:

$$P(S_t<S^* \mid S_{t-1}) \leq b \qquad (5)$$

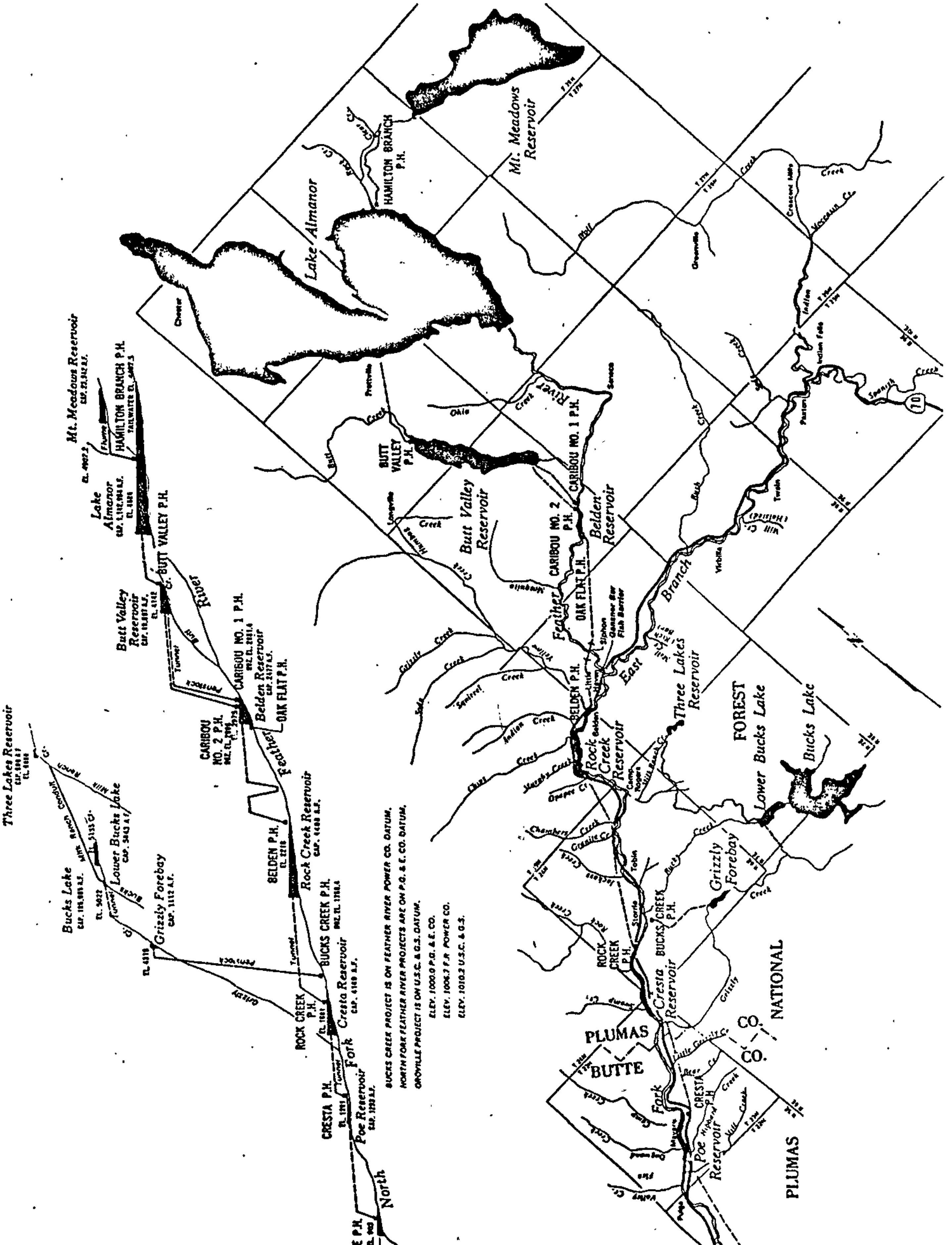

Figure 3. The North Fork Feather River Watershed

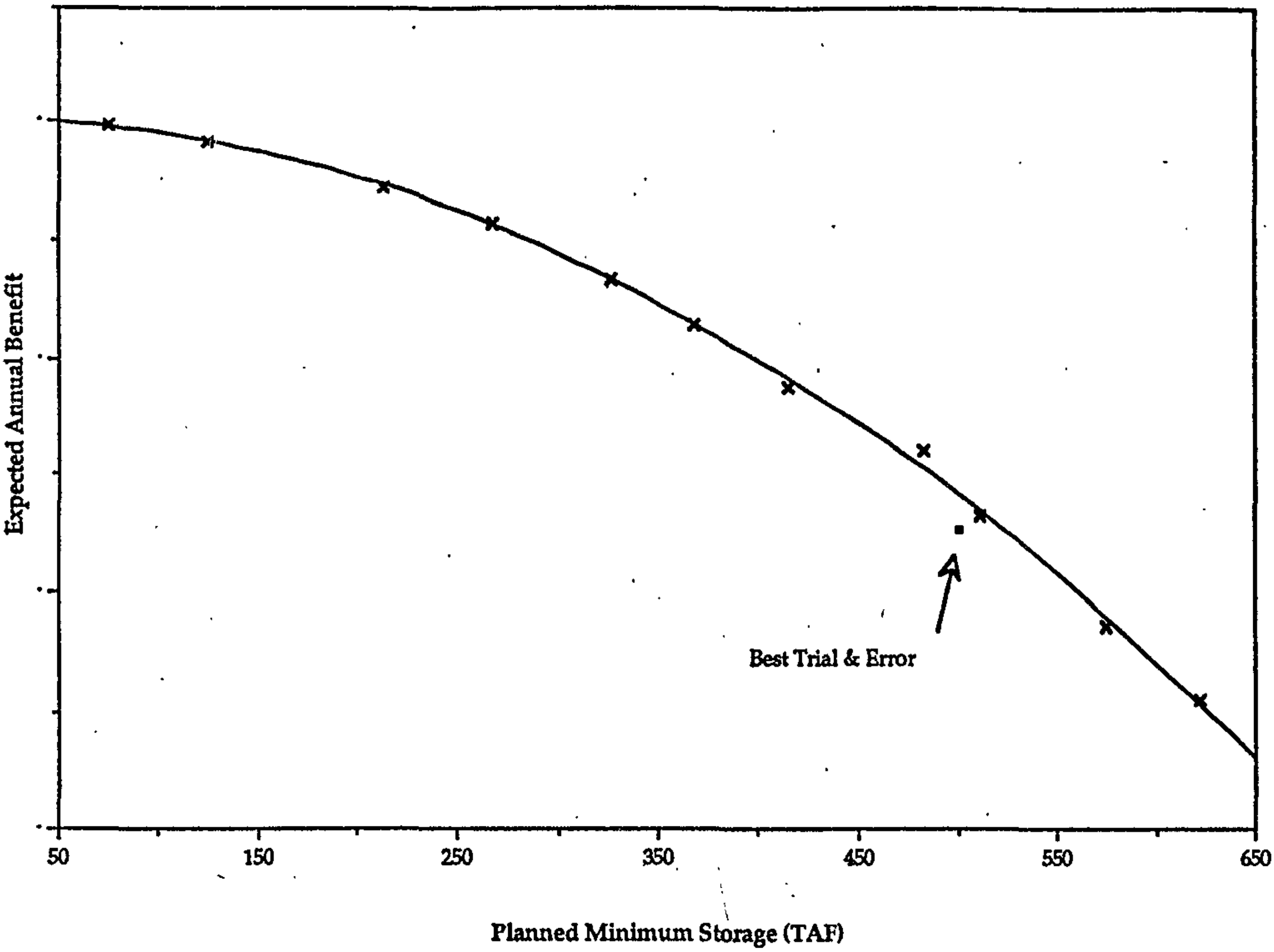

Figure 4. Benefit Variation with Minimum Storage

where b is the maximum allowed chance of violating the constraint. (1-b) could be considered the water level reliability. Using this approach, no bound is actually placed on the unconditional probability that S_t will be less than S^*. Only a policy that avoids such situations is generated.

In applying the constraint, the SSDP algorithm rejects any possible target release in stage t-1 for which the frequency of streamflow scenarios where S_t)<S^* is greater than b. As a result, the expected annual benefit of energy production varies with b. For example, experimental results of the planning models for the NFFR system with t=8 and S^*=900 TAF, indicate a potential benefit increase of about 1% when b=0.3 compared to the results with b=0. Without any constraint (b=1), the benefit increase could be as high as 10%.

Conclusion

SSDP is a suitable approach for developing optimal rule curves for the water and power model. It can capture important characteristics of a river basin, such as the minimum storage level. Futhermore, it can be used to assess the impact of a probabilistic constraint such as water level reliability on expected reservoir benefits.

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