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ARTIFICIAL NEURAL NETWORKS APPLIED TO RESERVOIR OPERATION

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1. INTRODUCTION

This study investigates the derivation of monthly reservoir operating policies by Implicit Stochastic Optimization (ISO) and Artificial Neural Networks (ANNs).

The ISO technique consists in generating synthetic inflow scenarios which are used by a deterministic optimization model to find optimal releases. The set of optimal releases are related to current reservoir storage and projected inflow in order to define operating rules. In contrast to the conventional use of regression analysis to obtain equations relating optimal releases to the other variables, this study uses ANNs to calculate the release to be implemented at each month. ANNs are capable to detect trends and extract patterns that are too complex to be noticed by either humans or other computer techniques[1)].

The procedure is used to find reservoir operating rules of Ishitegawa Dam, reservoir which supplies the city of Matsuyama in Japan.

2. DETERMINISTIC OPTIMIZATION MODEL

It is assumed that the main objective of the operation is to find the allocations of water that best satisfy the respective demands without compromising the system. Another aim is to keep the storage high whenever possible, i.e., every time there exists alternative optimal solutions for the releases. The objective function of the optimization problem is thus written as follows:

$$\min \sum_{t=1}^{N} \left\{ \left[\frac{R(t)-D(t)}{D(t)} \right]^2 + \left[\frac{S(t)-S_{\max}}{S_{\max}} \right]^2 \right\} \qquad (1)$$

where t is the time index; N is the operating horizon; $R(t)$ is the release during period t; $D(t)$ is the demand during period t; $S(t)$ is the reservoir storage at the end of time interval t; and $S_{\max}$ is the storage capacity of the reservoir.

Release and storage at each period are related to inflow and spill through the continuity equation:

$$\begin{aligned} S(1) &= S_0 + I(1) - R(1) - Sp(1) \\ S(t) &= S(t-1) + I(t) - R(t) - Sp(t); \quad t = 2, \ldots, N \end{aligned} \qquad (2)$$

in which S_0 is the initial reservoir storage; $I(t)$ is the inflow during time t; and $Sp(t)$ is the spill that eventually might occur during time t.

The physical limitations of the system define intervals which release, storage and spill must belong to:

$$0 \le R(t) \le \min[D(t), R_{\max}]; \quad \forall t \qquad (3)$$

$$S_{dead} \le S(t) \le S_{\max}; \quad \forall t \qquad (4)$$

$$0 \le Sp(t) \le Sp_{\max}; \quad \forall t \qquad (5)$$

where $R_{\max}$ is the maximum possible release; S_{dead} is the dead storage; and $Sp_{\max}$ is a maximum value set to the volume of spillage.

3. IMPLICIT STOCHASTIC OPTIMIZATION PROCEDURE

The ISO procedure has the three basic steps described below:

1) Generate M synthetic N-month sequences of inflow;
2) For each inflow realization, find the optimal releases for all N months by the deterministic optimization model (1)-(5);
3) Use the ensemble of optimal releases ($M \times N$ data) to develop operating rules for each month of the year.

The releases obtained by the optimization model, $R(t)$, are related to reservoir storage at the end of the previous time period, $S(t-1)$, and inflow during the current time period, $I(t)$. One relationship (rule) is determined for each month of the year. Therefore, with information of initial reservoir storage and forecasted inflow for the current month, the amount of water that should be released can be defined by the particular rule.

The relationships are established by ANNs. Thus, the release for any condition of storage and inflow can be found by accessing the corresponding ANN.

Like the optimization model (1)-(5) and the ISO procedure, the ANNs for each month were constructed in MATLAB.

4. ARTIFICIAL NEURAL NETWORK MODEL

The model scheme for each month is a multilayer feed-forward ANN formed by three layers. Figure 1 illustrates the topology of the ANN model. The number of nodes (neurons) in the hidden layer is determined applying a trial-and-error procedure. The best training results were achieved with 20 nodes.

In this network, each element of the input vector (forecasted inflow and initial reservoir storage) is connected to each neuron in the hidden layer. The ith neuron in the hidden layer has a summation that gathers its weighted inputs and bias to form its own scalar output or

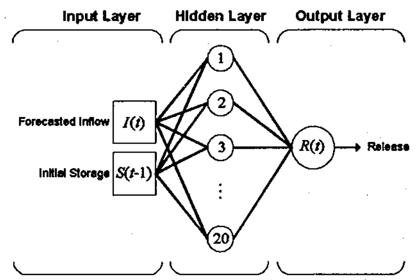

Figure 1. Topology of the ANN model.

induced local field. Each induced local field is submitted to an activation function so that they become the inputs of the output layer. The unique neuron in the output layer also has a summation that gathers its weighted inputs (from the hidden layer) and bias to form its induced local field. This induced local field is then submitted to the neuron activation function and becomes the final output or release. A tan-sigmoid function is chosen as the activation function of hidden nodes and a linear activation function is used for the output layer neuron.

The ANN training is performed by the well-known back-propagation algorithm[1] which has been successfully applied to water resources systems. The network training is supervised, i.e., the series of weights between the neurons and the bias are adjusted through the iterations (epochs) in order to fit the series of inputs to another series of known outputs. After 1000 epochs the training is terminated.

5. RESULTS AND DISCUSSION

The ISO procedure was applied to the Ishitegawa Dam reservoir which supplies the city of Matsuyama. The maximum reservoir storage (S_{max}) was assumed to be only 8,500,000 m^3, different from the actual capacity of 12,800,000 m^3, because it was desired to observe many shortage situations and then compare how they are handled by the models.

The ISO process was run under an operating horizon of 288 months (24 years). 100 sequences of synthetic monthly inflow data were generated by the non-stationary autoregressive model of Thomas-Fiering[2]. The initial storage was set to S_{max}. The first and last two years of data were rejected to avoid problems with boundary conditions. This provided 24,000 optimal monthly releases.

The data of releases, initial storages and inflows for the months of January through December were grouped and trained by the ANN model described in Section 4. For each month, a trained ANN was established and the corresponding values of releases were obtained by their use. This process generated 12 ANNs, one for each month.

After the definition of the release rules, they were applied to a new realization of 10 years of monthly inflows and compared to the results obtained from the utilization of the deterministic optimization model assuming the inflows as perfect forecasts. The operation of the system using the perfect-forecast situation gives us the "ideal" releases that should be employed for all 10 years since it has knowledge of all future inflow values. In addition, simulations based on the so-called *Standard Linear Operating Policy*[3] or SLOP were used for comparison. The SLOP states that when the available water is equal or less than the demands, all storage water is released; and when the available water exceeds the demands, the excess is stored in the reservoir until its maximum capacity is reached and spillage starts to occur.

Figure 2 shows the results for the period between the fourth and eighth years within the 10-year series. The correlation regarding water allocation between the results obtained by the ISO-ANN-generated rules and optimization under perfect forecast was 93%. The correlation of SLOP with optimization was only 71%. Comparing the results from the optimization under perfect

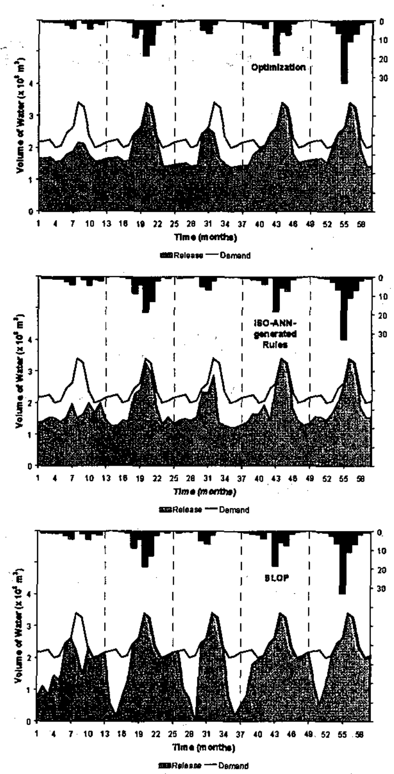

Figure 2. Results for the period between the fourth and eighth years within the 10-year series.

forecast with the ones from the SLOP it can be noticed that the optimization model tries to mitigate the great concentrated deficits that happen with the SLOP by decreasing the releases prior to shortage periods so that the overall deficit also diminishes.

Examinations of Figure 2 show us that the simulation using the ISO-ANN-generated rules tries to allocate water in a way very similar to the optimization under perfect forecast. This information indicates that the results from the derived release policies were quite satisfactory given the fact they have information only on the previous reservoir storage and current inflow whereas the optimization model has knowledge of inflows for the whole operating horizon and thus better means to define superior policies.

4. CONCLUSIONS

In this study, monthly operating rules were defined by Implicit Stochastic Optimization and Artificial Neural Networks. These rules showed capable to produce policies relatively equivalent to the ones found by optimization under perfect forecast. Thus, such procedure may be useful in the decision-making process of reservoir operation.

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