USE OF MONTE CARLO OPTIMIZATION AND ARTIFICIAL NEURAL NETWORKS FOR DERIVING RESERVOIR OPERATING RULES

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This paper deals with the use of Monte Carlo optimization and Artificial Neural Networks (ANNs) for deriving monthly reservoir operating rules. The procedure generates synthetic inflow scenarios which are used by a deterministic optimization model to find optimal releases. The ensemble of optimal release data is related to storage and inflow in order to form allocation rules. Different from the common use of regression analysis to define equations relating releases to the other variables, this paper uses ANNs to calculate the releases to be implemented at each period. Simulations based on the use of numerical interpolation instead of ANNs are used for comparison. The procedure is applied to the multipurpose reservoir that supplies the city of Matsuyama in Japan and the results show high correlation with those using optimization under perfect forecast.

Key Words **:** *Artificial neural networks, Monte Carlo optimization, reservoir operation.*

1. INTRODUCTION

Nowadays the simple use of hydrological records to solve problems of reservoir operation has been outdated. As the management problems are more and more multi-criterial, new techniques and algorithms have arisen as powerful tools for modeling several problems regarded to water sciences.

The first approaches that applied Monte Carlo procedures to solve reservoir operating problems consisted in defining release policies by least square multiple regression. The optimal releases were found by an optimization model and then regressed on the current reservoir storage and projected inflow. The regression equation could be thus used to obtain the reservoir releases at any time given the present storage and inflow[1)]. However, according to Willis et al.[2)], release-storage-inflow relationships often reveal nonlinear trends and therefore simple regression analysis are not appropriate. Celeste et al.[1)] considered the nonlinear trends and related these variables through numerical interpolation.

In a tentative of extracting the most complex nonlinear trends that exist in the relationships among optimal release, storage and inflow, this study relates these variables by using the so-called Artificial Neural Networks (ANNs).

ANNs appear to extract patterns and detect trends that are too complex to be noticed by either humans or other computer techniques. Different from conventional computer models, which use an algorithmic approach (set of instructions in order to solve a problem), ANNs process information in a similar way the biological nervous system does. The network has a large number of highly interconnected processing elements (neurons or nodes) working in parallel to solve a specific problem. Each of these interconnections has a weight that shows its importance. This tool learns through examples selected carefully and the most important characteristics that make neural networks attractive are: good for nonlinear systems, interacting with data from the environment, fault tolerance, adaptation to circumstances, etc[3),4)].

A Monte Carlo procedure using a quadratic optimization model and ANNs are applied to derive monthly operating rules for the reservoir that supplies the city of Matsuyama in Japan. Matsuyama suffers with lack of water and consequently there is a great necessity of a better management and development of the water resources in the region.

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:

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

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

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

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. MONTE CARLO PROCEDURE

The Monte Carlo 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, $S(t\text{-}1)$, 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 Artificial Neural Networks. Thus, the release for any condition of storage and inflow can be found by accessing the corresponding network. It is to be noticed that no equation is necessary and the allocations are determined only through the ANNs.

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

4. ARTIFICIAL NEURAL NETWORK MODEL

The model scheme is a multilayer feed-forward Artificial Neural Network trained by the well-known back-propagation algorithm. This model is responsible for deriving the monthly reservoir operating rules from the optimal results obtained by the optimization model.

(1) Architecture

The architecture of the network for each month is formed by the input layer, one hidden layer and the output layer. The input layer is composed by two nodes (neurons), which are the forecasted inflow and the initial reservoir storage for the current month.

The number of neurons in the hidden layer is determined based on several factors such as training accuracy, computation velocity, etc. Considering these factors and by means of a trial-and-error procedure, the best training results were achieved with 20 neurons in the hidden layer. The amount of water to be released is the single neuron of the output layer.

(2) Topology

The principal importance of a neural network is not only the way nodes are implemented but also how their interconnections (topology) are made. In this study the network topology is constrained to be feed-forward, i.e., the connections are allowed from the input layer to the hidden layer and from the hidden layer to the output layer. **Figs. 1** and **2** illustrate the network topology of this study and the details of a neuron, respectively.

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 *i*th neuron in the hidden layer has a summation that gathers its weighted inputs and bias to form its own scalar output or 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.

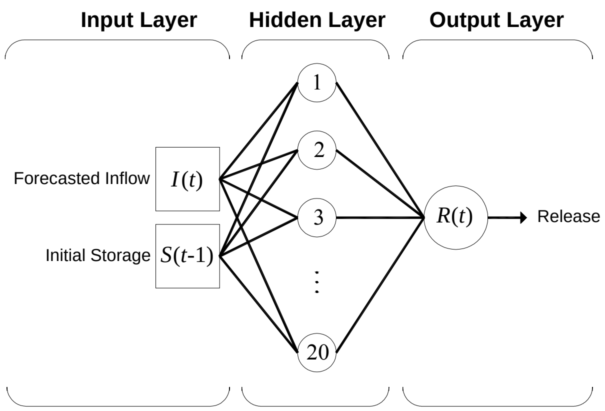

Fig. 1 Topology of the Artificial Neural Network.

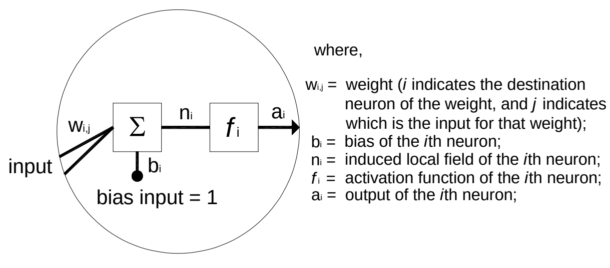

Fig. 2 Details of a neuron.

(3) Activation functions

Continuous and differential functions are necessary for relating inputs and outputs of the ANNs. According to Haykin[4] the sigmoid function (a nonlinear, continuous and differential function) is a good activation function for each neuron due to its generally accepted behavior. The tan-sigmoid function is chosen as the activation function for the hidden neurons. For the output layer neuron, a linear activation function is used. This happens because the tan-sigmoid function can produce outputs only between minus one (-1) and plus one (+1) and the desired results are outside this range.

(4) Training process

The training is performed by the well-known back-propagation algorithm which has been successfully applied to water resources systems. In this approach, the Scaled Conjugate Gradient (SCG) method is used for the back-propagation. A detailed explanation of the SCG method is provided by Moller[5]. 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. The training also occurs in the batch mode. In this mode the weights and biases are updated only after the entire training set has been applied to the network. After 1000 epochs the training is terminated.

(5) Data adjustment before training

Two preprocessings are performed on the data to improve the efficiency of the ANNs.

The *Early Stopping* method is applied to the original data for improving generalization. This technique avoids a problem called overfitting that occurs during the neural network training. The network seems to be very well trained by showing very small errors from the training set data, but when new inputs are used the error is large[6].

To make the ANNs more efficient the *Min and Max Preprocessing* is performed on the network inputs and outputs. They are scaled so that they always try to fall within a specific range. For this, two new data were added in the training data to establish two boundary conditions: 1) minimum storage and minimum inflow implies no release; 2) maximum storage and maximum inflow implies maximum release.

5. APPLICATION AND RESULTS

The Monte Carlo procedure was applied to the Ishitegawa Dam reservoir which supplies the city of Matsuyama, located in Ehime Prefecture, Japan. The reservoir is also used for irrigation and flood control. 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 Monte Carlo 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[7)]. 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. **Figs. 3-5** show the scatter graphs of ANN releases (obtained by the inflow and storage training data) and training data releases for May, July and September, respectively. These graphs reveal the good accuracy reached by the ANNs.

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 numerical interpolation of the data ensemble were used for comparison.

Fig. 6 shows the results for the period between the fourth and eighth years within the 10-year series. **Fig. 7** displays the relationships of the ideal releases found by the optimization under perfect forecast against the releases obtained by ANNs and numerical interpolation.

The correlation regarding water allocation between the results obtained by the ANN-generated rules and optimization under perfect forecast was 95%. The correlation of the numerical interpolation with optimization was 92%.

Examinations of **Figs. 6** and **7** show us that the simulation using the Monte Carlo-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.

Comparing the results from the Monte Carlo-generated rules using ANNs with the ones using numerical interpolation it can be noticed that ANNs’ capabilities in adapting to circumstances and identifying nonlinear trends produce more reliable results than pure data interpolation.

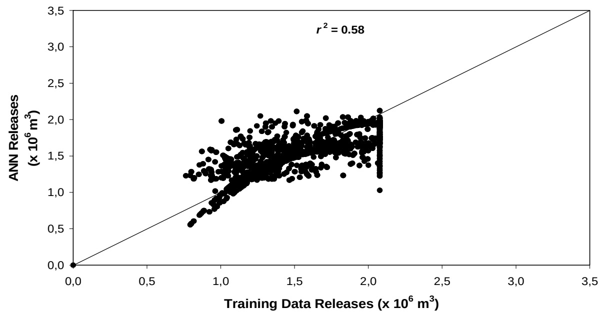

Fig. 3 Scatter graph of ANN releases and training data releases for May.

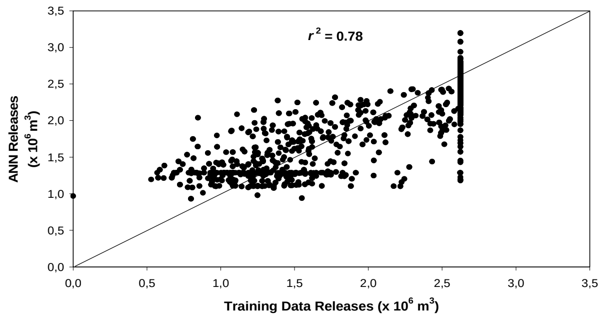

Fig. 4 Scatter graph of ANN releases and training data releases for July.

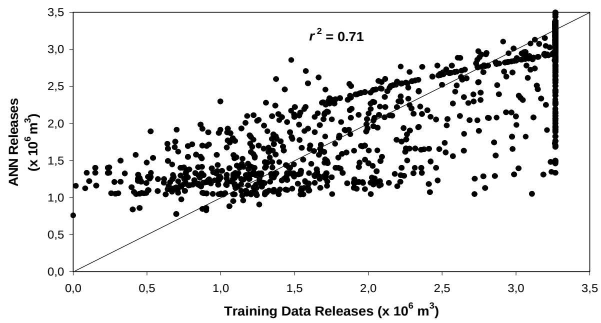

Fig. 5 Scatter graph of ANN releases and training data releases for September.

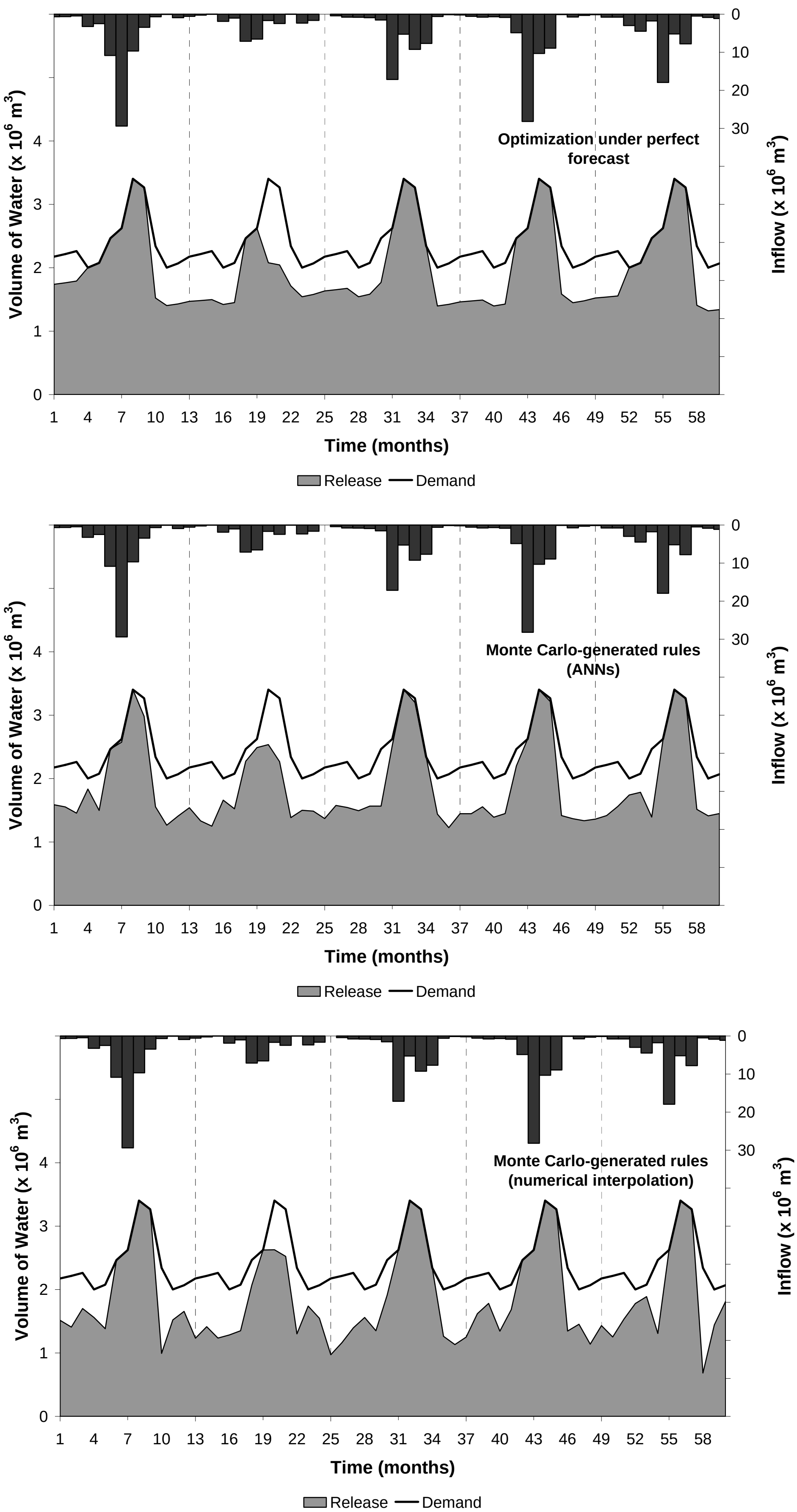

Fig. 6 Results for the period between the fourth and eighth years within the 10-year series.

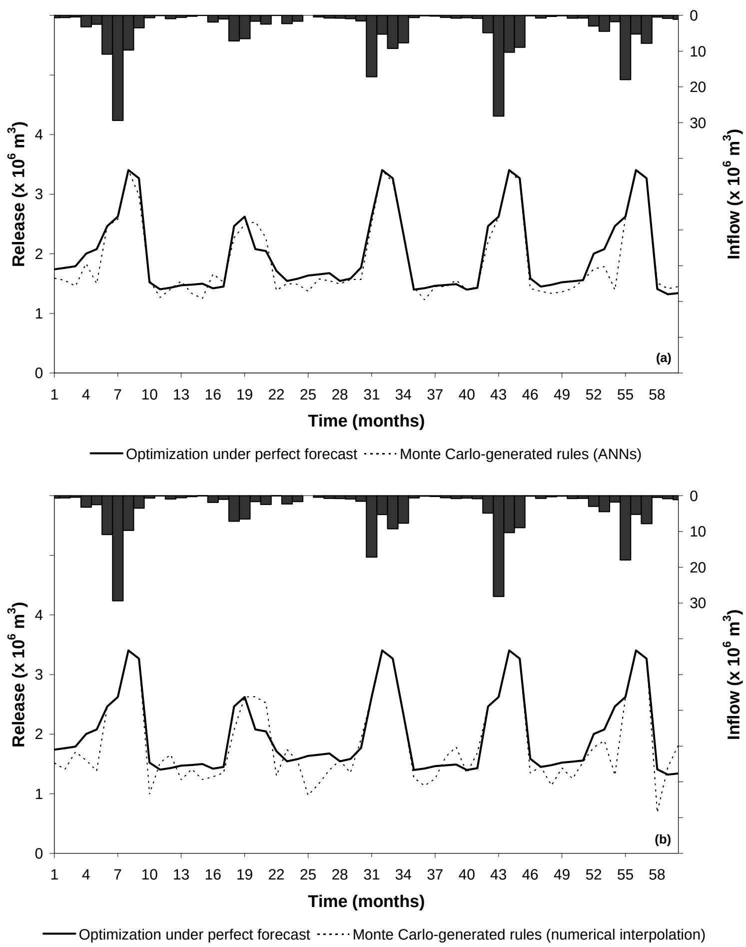

Fig. 7 Correlations of releases obtained (a) by optimization under perfect forecast and Monte Carlo-generated rules using ANNs; and (b) by optimization under perfect forecast and Monte Carlo-generated rules using numerical interpolation.

6. CONCLUSIONS

In this study, Monte Carlo Optimization and Artificial Neural Networks were applied to define monthly operating rules for a multipurpose reservoir in Japan. The procedure solved a number of quadratic deterministic optimization models, each of which with a given realization of reservoir inflows, and then used the generated data and ANNs to construct optimal release-storage-inflow relationships for every month. These relationships were afterward utilized as a basis to simulate new operations and showed capable to produce policies relatively equivalent to the ones found by optimization alone.

The results also suggest that ANNs are more reliable than numerical interpolation for finding release policies. They revealed that ANNs are very good in interacting with data from the environment and identifying nonlinear trends.

Thus, such procedure may be useful in the decision-making process of reservoir operation.

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