Daily reservoir operating rules by implicit stochastic optimization and artificial neural networks in a semi-arid land of Brazil

CAMILO ALLYSON SIMÕES DE FARIAS[1], CELSO AUGUSTO GUIMARÃES SANTOS[2] & ALCIGEIMES BATISTA CELESTE[3]

1 *Academic Unit of Environmental Science and Technology, Federal University of Campina Grande, Rua Jairo Vieira Feitosa, S/N, Pereiros, 58840-000 Pombal – PB, Brazil*
camiloallyson@yahoo.com.br

2 *Dept of Civil and Environmental Engineering, Federal University of Paraíba, 58051-900 João Pessoa – PB, Brazil*

3 *Dept of Civil Engineering, Federal University of Sergipe, Av. Mal. Rondon, S/N, Jardim Rosa Elze, 49100-000 São Cristóvão – SE, Brazil*

Abstract This paper presents a model based on Implicit Stochastic Optimization (ISO) and Artificial Neural Networks (ANN) for deriving daily operating rules for a reservoir system located in a semi-arid region of Brazil. The ISO procedure consists of optimizing the reservoir system for possible inflow scenarios and then analysing the optimal outcomes in order to generate operating rules. Unlike the common use of regression equations, this study makes use of ANN to develop reservoir hedging rules relating end-of-period reservoir storage to initial storage and other system variables. After the establishment of the ISO-ANN rules, they were tested over a new series of inflows and the outcomes were assessed by means of sustainability criteria. The ISO-ANN rules were shown to be superior to the so-called Standard Linear Operating Policy (SLOP) and equivalent to the results derived by deterministic optimization taking the same inflows as perfect forecasts for one year ahead.

Key words reservoir operation; artificial neural networks; implicit stochastic optimization; hedging rules; sustainability; semi-arid

INTRODUCTION

Human activities and development plus the uneven distribution of the water resources on Earth are the main causes of water-related problems. Some regions have it in abundance and suffer with floods; some of them experience water lack and shortages; and others have to face problems caused by its poor quality (Loucks, 2000). Factors such as population growth, climate oscillation, increasing demands and environmental considerations are responsible for increasing the complexity in the water resources planning and management (Nandalal & Bogardi, 2007). In a semi-arid region, which is the case of northeastern Brazil, the situation is aggravated by the irregular space–time distribution of precipitation, and high evaporation rates. The drought-related problems in semi-arid regions may be mitigated by an adequate water system management capable of taking into account the hydrologic uncertainties. Implicit Stochastic Optimization (ISO) procedures are techniques that implicitly consider this variability (Reddy, 1987; Farias, 2009).

This paper consists of developing a model based on ISO and Artificial Neural Networks (ANN) for deriving daily operating rules for a reservoir system located in Paraíba State, semi-arid region of Brazil. Artificial neural networks process information in the same way as the biological nervous system and are capable of extracting and detecting the most complex nonlinear trends among the variables being evaluated (Haykin, 1999; Farias, 2009).

SYSTEM DESCRIPTION

The case study is the Coremas-Mãe D'água water system, which is located in southwestern Paraíba, Brazil. The system is composed of two reservoirs connected by a canal with a flow capacity of 12 m^3/s. Coremas Reservoir, with a capacity of 720 000 000 m^3, is fed by two tributaries: River Piancó (main) and River Emas. The Mãe d'Água Reservoir has a capacity of 638 700 000 m^3, and dams up the River Aguiar. The main uses of the system include water for

Copyright © 2011 IAHS Press

domestic, irrigation and industrial use; and fish farming. The Coremas Reservoir is also used for hydropower generation.

According to Celeste *et al.* (2009), the mathematical implementation of Coremas-Mãe D'água is complicated due to the water transfer between both reservoirs. In order to simplify the application of the models developed in this study, the Coremas-Mãe D'água water system is modelled as an equivalent reservoir. Therefore, the sum of the active storages of the individual reservoirs is the active storage of the equivalent reservoir. Considering the limited quantity of observed inflow data for River Aguiar and the fact that the rivers Piancó and Emas are responsible for the most part of the system inflows (81.2%), the inflows to the equivalent reservoir were assumed to be the sum of River Piancó and River Emas inflows.

HEDGING RULES BY IMPLICIT STOCHASTIC OPTIMIZATION AND ARTIFICIAL NEURAL NETWORKS

Deterministic optimization model

This model assumes that the main objective of the operation is to find the allocations of water that best satisfy the total demands without compromising the system. The operation is derived for 365 days ahead and the objective function of the optimization problem is written as follows:

$$\text{minimize} \sum_{t=1}^{N} \left[\frac{R(t) - D(t)}{D(t)} \right]^2 \tag{1}$$

where N is the operating horizon; t is the day index; $R(t)$ is the reservoir release during day t; and $D(t)$ is the demand during day t.

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

$$S(1) = S_0 + I(1) - R(1) - Sp(1)$$

$$S(t) = S(t-1) + I(t) - R(t) - Sp(t); \quad \forall t = 2, \ldots, N \tag{2}$$

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

The physical limitations of the system define lower and upper bounds for releases, storage and spill:

$$0 \leq R(t) \leq D(t); \quad \forall t \tag{3}$$

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

$$Sp(t) \geq 0; \quad \forall t \tag{5}$$

where $S_{\max}$ and S_{dead} are the maximum and dead reservoir storage, respectively.

This procedure is executed and the optimal releases for 365 days are found. However, only the release for the current day is used. The process is repeated for the next day and so forth until the final day of operation is reached.

This optimization model is formulated as a quadratic programming problem with linear constraints and it is implemented in the MATLAB© environment.

Implicit stochastic optimization procedure

The ISO procedure of this study has the three basic steps described as follows:

– generate M synthetic daily sequences of reservoir inflows;
– optimize the system operation for all M sequences using the deterministic optimization model with equations (1)–(5);

– use the ensemble of optimal outcomes to develop reservoir storage hedging rules.

The end-of-period reservoir storage $S(t)$ is related to reservoir storage at the previous time period $S(t-1)$, total demand during the current time period $D(t)$, and reservoir inflow during the current time period $I(t)$. Therefore, with information on initial reservoir storage, total demand, and inflow for the current day, the end-of-period amount of water that should be kept in the reservoir can be defined by the hedging rules, which are established by an ANN.

ISO-ANN hedging rules

A multilayer feed-forward ANN is responsible for deriving reservoir storage hedging rules based on the optimal results obtained by the application of the ISO procedure.

Architecture, topology and activation functions The architecture of the network is formed by the input layer, one hidden layer and the output layer. The input layer is composed of four neurons, which are the initial reservoir storage $S(t-1)$, current reservoir inflow $I(t)$, and current total demand $D(t)$. The number of four neurons in the hidden layer was determined based on a trial-and-error procedure. The end-of-period reservoir storage $S(t)$ is the single neuron of the output layer. The network topology is shown in Fig. 1. The tan-sigmoid and linear functions were chosen as the activation functions for the hidden and output neurons, respectively.

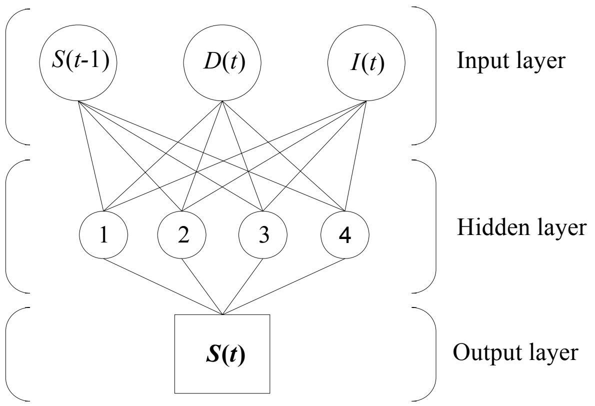

Fig. 1 Topology of the ANN model responsible for determining the hedging rules.

Training process The training is performed by the back-propagation algorithm, which has been successfully applied to water resources systems (Haykin, 1999). In this approach, the Levenberg-Marquardt (LM) algorithm is used for the back-propagation training. A detailed explanation of LM algorithm is provided by Hagan & Menhaj (1994). In order to improve generalization, the ANN training is stopped by the Early Stopping Method (Demuth & Beale, 2005).

Short-term optimization using the ISO-ANN hedging rules

This model incorporates the ISO-ANN hedging rules into the objective function of the problem, which is formulated as follows:

$$minimize \sum_{t=1}^{CN} \left\{ \alpha_1 \left[\frac{R(t)-D(t)}{D(t)} \right]^2 + \alpha_2 \left[\frac{S(t)-S_{\text{targ}}(t)}{S_{\text{targ}}(t)} \right]^2 \right\} \tag{6}$$

subject to

$$S(1) = S_0 + I(1) - R(1) - Sp(1)$$

$$S(t) = S(t-1) + I(t) - R(t) - Sp(t); \quad \forall t = 2,\ldots,N \tag{7}$$

$$0 \le R(t) \le D(t); \quad \forall t \tag{8}$$

$$S_{\text{dead}} \le S(t) \le S_{\max}; \quad \forall t \tag{9}$$

$$Sp(t) \ge 0; \quad \forall t \tag{10}$$

where CN is the short-term operating horizon, $S_{\text{targ}}(t)$ is the target reservoir storage at period t, α_1 is the priority coefficient for the first term of the objective function; and α_2 is the priority coefficient for the second term of the objective function.

The CN-step-ahead target reservoir storages S_{targ} are obtained by the recursive application of the ISO-ANN hedging rules using short-term forecasts of inflows for the next CN days. During the real time operation, the short-term optimization model finds the optimal releases for CN days ahead; however, only the allocation for the current day is used. The procedure is repeated for the next day and so forth until the final day of operation is reached.

RISK INDEXES

Different kinds of risk criteria have been studied in order to identify the sustainability of water supply reservoirs. Hashimoto *et al.* (1982) proposed three indicators (reliability, resiliency and vulnerability) aimed at verifying the possible performance of alternative operating policies for water resources systems. This study makes use of the reliability and vulnerability indexes in order to evaluate the performance of the applied procedures.

Reliability

This indicator evaluates how probable a system is to not fail. Mathematically, the reliability can be defined as the probability of a system being in a satisfactory state within the operating horizon, i.e. it is the percentage of time in which the system works without failures:

$$\beta = P\{X(t) \in ST\} = 1 - \frac{NF}{n} \tag{11}$$

where β is the reliability; $X(t)$ is a temporal series conditioned to time index t ($t = 1, 2, \ldots, n$); ST is the satisfactory state; NF is the number of time intervals in which failures occur; and n is the total number of time intervals.

Vulnerability

This index assesses how great the magnitude of the system's failures can be. The vulnerability can be defined as follows:

$$\gamma = \frac{1}{NF} \sum_{i=1}^{NF} s(i) \tag{12}$$

where γ is the vulnerability and $s(i)$ is the deficit volume of the ith failure event.

APPLICATION AND RESULTS

For the application of the ISO-ANN hedging rules, the short-term operating horizon was set to 5 days (N = 5 d). The reservoir inflows for this operating horizon were assumed to be reliable since accurate meteorological forecasts are generally available. The priority coefficient α_2 was kept superior to α_1 ($\alpha_1 = 1$ and $\alpha_2 = 500$). As a consequence, the target storages were given priority over the option of attending water demands.

The ISO process was run under an operating horizon of 36 500 days (100 years). The sequences of reservoir inflows for Piancó and Emas rivers were generated by the first-order autoregressive (AR-1) multivariate model suggested by Matalas (1967), which successfully incorporated the statistical features of the historical data into the generated values, as can be seen in the results for River Emas in Fig. 2(a). This provided 36 500 days of optimal daily reservoir storages. The data of initial reservoir storages, total demands, inflows, and end-of-period storages were grouped and trained by the ANN model.

In order to verify the performance of the procedures at different scenarios, a new five-year realization (1825 days) of synthetic reservoir inflows were generated by the multivariate AR-1 model. The ISO-ANN hedging rules were applied to the operation of the system and compared to the results obtained from the utilization of the deterministic optimization model using perfect forecasts for 365 days ahead. The operation using the deterministic model gives us the "ideal" releases that should be employed since it has knowledge of future inflows for one year ahead. Additionally, a simulation based on the so-called Standard Linear Operating Policy (SLOP) was used for comparison. The SLOP states that the demands should be met whenever possible (Loucks *et al.*, 1981). The water allocation results are displayed in Fig. 2(b)–(d).

Examination of Figs 2(b)–(d) show us that the operation using the ISO-ANN rules tries to allocate water in a way very similar to the deterministic optimization model. This information indicates that the results from the derived policies were quite satisfactory, because they have information only on the previous reservoir storage and forecasts of reservoir inflows for five days ahead, whereas the deterministic optimization model has knowledge of forecasts for one year ahead and thus better means to define superior policies. Comparing the results from the deterministic model with the SLOP, it can be seen that the optimization model tries to mitigate the great concentrated deficits that happen with the simulation by decreasing the releases prior to shortages periods so that the overall deficit also diminishes.

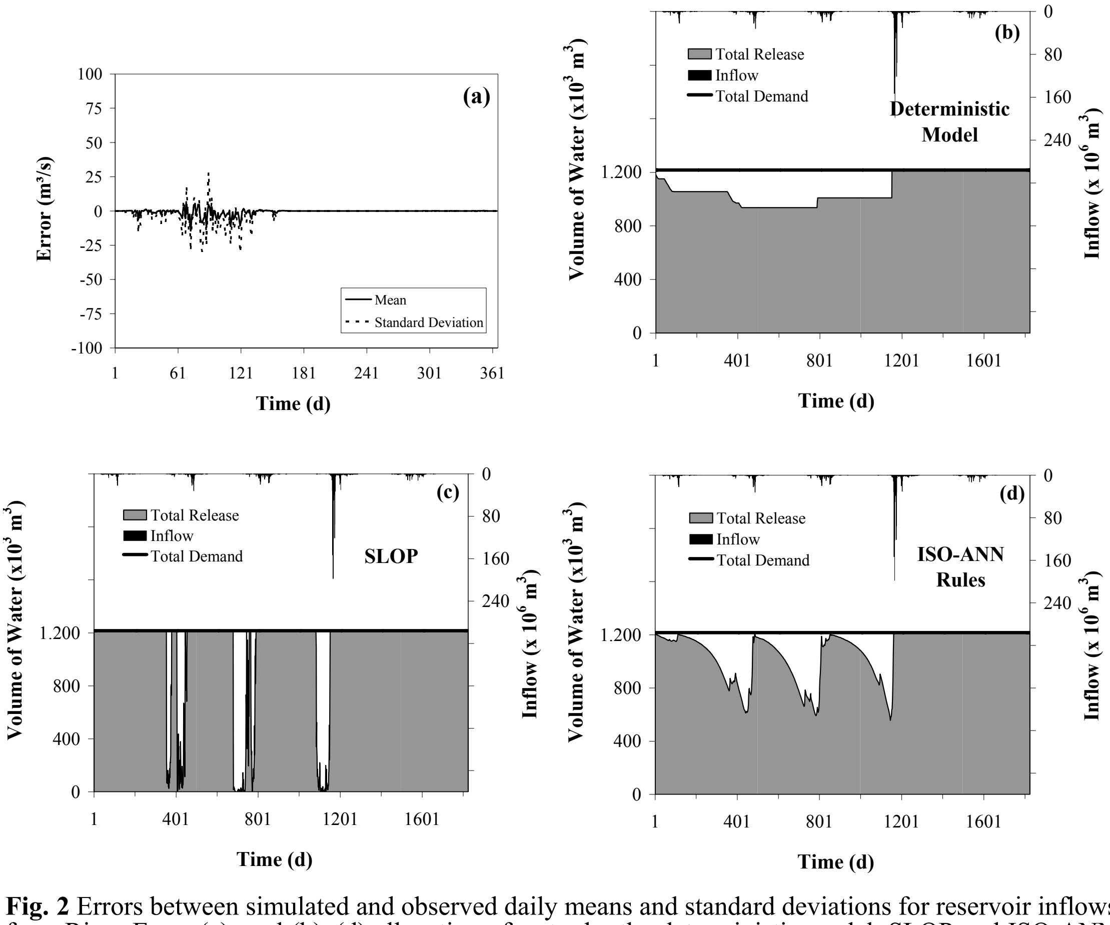

Fig. 2 Errors between simulated and observed daily means and standard deviations for reservoir inflows from River Emas (a); and (b)–(d) allocation of water by the deterministic model, SLOP and ISO-ANN rules.

Risk indexes were used in order to evaluate the performance of the system along the temporal series of releases. The satisfactory state was conditioned to the releases of the desired demands. The risk indexes were analysed for various levels η of the demands (η = 5%, 10%, …, 100%). Therefore, for a given η, a failure state occurred when the releases were less than η percent of the respective demand. In this study, the vulnerability index for each period was calculated by the quadratic deviation between releases and demands:

$$\gamma(t) = \begin{cases} \left[\dfrac{R(t) - \eta D(t)}{\eta D(t)}\right]^2, & \text{if } R(t) < \eta D(t) \\ 0, & \text{if } R(t) \geq \eta D(t) \end{cases} \tag{13}$$

The vulnerability of the system γ is obtained as follows:

$$\gamma = \frac{1}{N} \cdot \sum_{t=1}^{N} \gamma(t) \tag{14}$$

The relative vulnerability γ_R is finally given by the following equation:

$$\gamma_R = \frac{\gamma}{\gamma_{\max}} \tag{15}$$

where $\gamma_{\max}$ is the highest value of vulnerability among all models and levels of demand.

The reliability and relative vulnerability results for all models and levels of demand are shown in Fig. 3. Investigations of Fig. 3(a) show that the deterministic model and the ISO-ANN rules were more reliable than SLOP for most of the demand levels, with the exception of those higher than 65%. This result was expected since the deterministic model and the ISO-ANN rules try to reduce the magnitude of deficits by decreasing releases prior to great shortages. Analyses of Fig. 3(b) suggest that both the deterministic model and ISO-ANN rules are much less vulnerable than SLOP for all levels of demand.

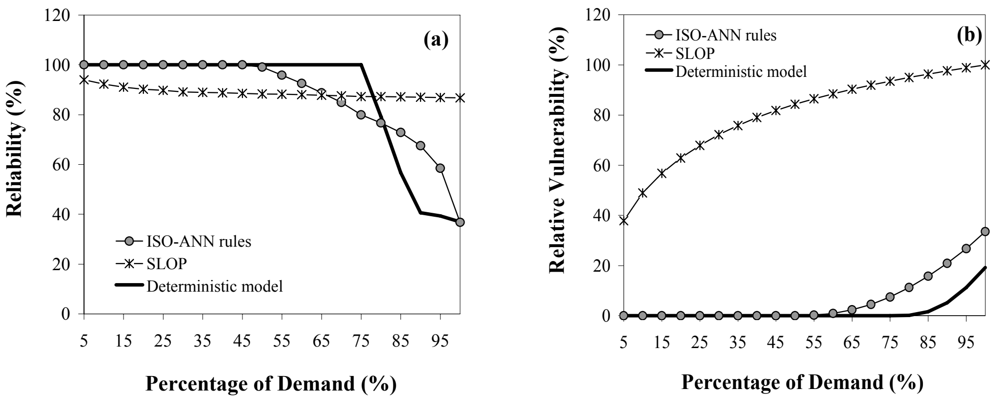

Fig. 3 Results for (a) reliability and (b) relative vulnerability.

CONCLUSION

A model based on Implicit Stochastic Optimization (ISO) and Artificial Neural Networks (ANN) was defined in order to devise operating rules to a water supply system located in a semi-arid land of Brazil.

The outcomes from the simulated operations were assessed by means of sustainability criteria and the results showed that the ISO-ANN hedging rules and the deterministic model generated more attractive policies than the standard rules of simulation. The results also indicated that the deterministic model produces the best policies for the system operation. However, since perfect forecasts for 365 days ahead are not available, the deterministic optimization model is not practical. On the other hand, the ISO-ANN rules presented results equivalent to the ideal ones and needs information only on the initial reservoir storage and forecasts for five days ahead. Consequently, the ISO-ANN rules may help in the decision making process for the operation of water systems under uncertainty in semi-arid regions.

Acknowledgements The authors thank the Brazil's National Council for Scientific and Technological Development (CNPq) for financial support.

REFERENCES

Celeste, A. B., Curi, W. F. & Curi, R. C. (2009) Implicit stochastic optimization for deriving reservoir operating rules in semiarid Brazil. *Pesquisa Operacional* **29**(1), 223–234.

Demuth, H. & Beale, M. (2005) Neural network toolbox: for use with Matlab. The MathWorks, Inc., Natick, USA.

Farias, C. A. S. (2009) Derivation of hedging rules and forecasts by artificial neural networks for optimal real-time management of an integrated water resources system. D. Eng. Thesis, Ehime University, Matsuyama, Ehime, Japan.

Hagan, M. T. & Menhaj, M. B. (1994) Training feedforward networks with the Marquardt algorithm. *IEEE Trans. Neural Networks* **5**(6), 989–993.

Hashimoto, T. Stedinger, J. R. & Loucks, D. P. (1982) Reliability, resiliency, and vulnerability criteria for water resource system performance evaluation. *Water Resour. Res.* **18**(1), 14–20.

Haykin, S. (1999) *Neural Networks: A Comprehensive Foundation*. Prentice-Hall, Upper Saddle River, USA.

Loucks, D. P. (2000) Sustainable water resources management. *Water International*, *IWRA* **25**(1), 3–10.

Loucks, D. P., Stedinger, J. R. & Haith, D. A. (1981) *Water Resources Systems Planning and Analysis*. Prentice Hall, USA.

Matalas, N. C. (1967) Mathematical assessment of synthetic hydrology. *Water Resour. Res.* **3**(4), 937–945.

Nandalal, K. D. W. & Bogardi, J. J. (2007) *Dynamic Programming Based Operation of Reservoirs: Applicability and Limits*, Cambridge University Press, Cambridge, UK.

Reddy, P. J. (1987) *Stochastic Hydrology*. Laxmi Publications, Delhi, India.