Continuous Decision Making in Optimal Reservoir Operation Using DP-ANN

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Abstract: According to desirable usage of water resources and because of large amount of existence dam in the world especially in Iran, optimum operation of these reservoirs and suitable operation rules is unavoidable. To achieve this goal and because of efficiency of Artificial Neural Networks (ANNs) in forecasting, this model was used to derive operation rules of reservoirs. In this paper, the amount of release in each period was calculated according to the storage of reservoir and the amount of inflow in the same period. We implied this methodology to Dez dam in west-south of Iran. The results were compared with regression model. Results show the high accuracy in this field of water resource management.

Key-Words: - Artificial Neural Networks, Dynamic Programming, Reservoir Optimal Operation.

1 Introduction

According to the deficiency and crisis of water in the world especially in Iran, necessity of optimum operation of water resources is unavoidable. And because of importance of problem, finding good and essential rules for operation of these reservoirs is vital. In this paper, we have tried to use a new way in every step of reservoir operating by assigning the water level and amount of demand at each period.

Achieving this aim, operation rule of reservoir for a specific duration was derived by dynamic programming. Output of this model was used as a set of train and test data for artificial neural networks model. Finally, with preparation of ANN model, the decision maker has the ability of deciding in each instance even with changing in inflow of reservoir, reservoir volume demands or a component of them is possible.

2 Artificial Neural Networks

Computational Intelligence (CI) is to extract algorithm from computational mathematics. An important characteristic of CI is being simple, accurate and flexible. Artificial Neural Networks, Fuzzy Logic and Genetic Algorithms are the components of CI. ANNs process data and try to learn the rule governing them.

The development of ANNs began in 1943 by Warren McCulloch and Walter Pitts. Then some effective researches on ANNs were carried out by different scientists such as Hebb, Rosenbellat, Widrow, Kohenon, Anderson, Grossberg and Carpenter. The fundamental revolution in this area, however, happened in 1980s by John Hopfield (1982) and then by David Rumelhart and James Mc Land who presented the Back Propagation Algorithm. Since then ANNs have found application in such different areas such as physics, neurophysiology, biomedical engineering, electrical engineering, robotics and others.

Since the early nineties, there has been a rapidly growing interest among water scientists to apply ANNs in diverse field of water engineering like rainfall-runoff modeling, stream flow and precipitation forecasting, water quality and ground water modeling, water management policy and so on. Some of applications of ANNs in stream flow and runoff forecasting are: application of ANN for reservoir inflow prediction and operation (Jain et al., 1999), river stage forecasting using artificial back propagation in neural networks [4], hydrological time series forecasting (Fuller and Lachtermacher, 1994), performance of neural networks in daily stream flow forecasting [11], daily reservoir inflow forecasting using artificial neural networks with stopped training approach [3], multivariate reservoir inflow forecasting using neural networks [2] temporal and finally comparative analysis of event-based rainfall-runoff modeling techniques-deterministic, statistical, and artificial neural networks (Jain and Indurthy, 2003).

2.1 Definition

An ANN is a massively parallel-distributed information-processing system that has certain performance characteristics resembling biological neural networks of human brain. A typical ANN is shown in "Figure 1".



Fig.1 A Typical Neural Network

Each neural network consists of three kind of layer: input, hidden and output layer and in every layer there are number of processors called nodes. Each node is connected to other neurons with a directed link and a special weight. Neurons' response is usually sent to the other ones. A set of inputs in the form of input vector \mathbf{X} is received by each unit and weights leading to the node form a weight vector \mathbf{W} . The inner product of \mathbf{X} and \mathbf{W} is *net* and the output of the node is f (net) as follow:

$$net = \mathbf{X}.\mathbf{W} = \sum x_i.w_i \tag{1}$$

$$out = f(net) \tag{2}$$

f is called activation function whose functional form determines response of the node to the input signal it receives. Two functions are usually used in different applications: sigmoid function and hyperbolic tangent, given as "Eq. [3]" and "Eq. [4]", respectively:

$$f(x) = \frac{1}{1 + e^{-x}}$$
(3)

$$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$
(4)

2.2 MLP Network

Multi Layer Perceptron is one of the most common networks. "Figure 2" shows the general format of this network. As it is seen each node in a layer is connected to all nodes in the previous layer (fully connected) and the output of a layer makes the input of the next one. Sigmoid and hyperbolic tangent functions and Back Propagation algorithm (BP) are usually used in a MLP network. It might be interesting to say that in %90 of ANNs' applications in hydrology MLP with BPA has been used [3].



Fig.2 A typical MLP network

Training of BP networks is carried out in three steps: 1)Presenting training sets to input and output neurons, 2)Computation of the error of the network and back propagating it, 3)Adjusting weights in order to reduce the error. There are some learning rules based on BP algorithm in MLP networks, and the most applicable one is Generalized Delta Rule. Weights are adjusted according to the "Eq. [5]"

$$\Delta w_{ij}(n) = -\alpha \cdot \frac{\partial E}{\partial w_{ii}} + \eta \cdot \Delta w_{ij}(n-1)$$
(5)

Where $\Delta w_{ij}(n)$ and $\Delta w_{ij}(n-1)$ are weight

increments between node *i* and *j* during the n^{th} and $(n-1)^{th}$ pass, or epoch. In equation (13), *a* and *h* are learning rate and momentum, respectively; and they are both useful for a better training process

2.3 Network Training

Training is a process by which the connection weights of an ANN are adapted through a continuous process of stimulation bv environment in which the net is embedded (ASCE). There are two types of network training: supervised and unsupervised. In a supervised method, the network with the input and desired output should be provided. Initially, the network will produce the wrong answer. Error (the difference between desired output and network's output) will be used to adjust the weights in the network so that the next time that the same example is presented, the response of the network would be a bit closer to the desired output. In unsupervised training method network is not given the desired response, but is left to organize the data in a way they see fit.

2.4 Providing Input Data

There are two important points in providing input data: mapping the training set into an appropriate interval and the way that training pairs are presented to a network. To avoid saturation problem, based on the activation function training, pairs should be mapped into a suitable interval (for sigmoid function into (0, 1) and for hyperbolic tangent into (-1, 1)). In addition, in order not to be trapped in a local minimum during the training process, training pairs should be presented to the

network randomly.

3 Case Study

We assumed reservoir of Dez dam in west south of Iran as a case study. 480 monthly release, demand and loss for each unit of surface are shown in Table1.

		Mar.	Apr.	Мау
Mean Inflow	МСМ	796	1151	1028
Mean Demand	МСМ	366	516	604
Mean Loss	mm/km2	1	82	189
		Jun.	Jul.	Aug.
Mean Inflow	МСМ	569	349	225
Mean Demand	МСМ	757	831	819
Mean Loss	mm/km2	272	269	280
		Sep.	Oct.	Nov.
Mean Inflow	МСМ	165	136	207
Mean Demand	МСМ	706	468	318
Mean Loss	mm/km2	275	116	94
		Dec.	Jan.	Feb.
Mean Inflow	МСМ	360	397	568
Mean Demand	МСМ	163	150	203
Mean Loss	mm/km2	-3	-47	-19

Table.1 Mean value of Inflow, Demand and Losses

In computing process, storage and surface of reservoir was discrete to 14 intervals. Beneficial storage of reservoir is 2510 MCM and its mean annual demand is 5900 MCM while mean annual inflow is 5951 MCM.

4 Methodology

In this section, following model was solved by dynamic programming.

The objective function is:

Minimize TSD =
$$\sum_{t=1}^{nt} (R_{(t)} - D_{(t)})^2$$
 (6)

And the restrictions are:

-Continuity equation:

$$R_{(t)} = S_{(t+1)} - S_{(t)} + I_{(t)} - Loss_{(t)} + Rein_{(t)}$$
(7)

-Storage limitation:

$$\mathbf{S}_{\min} < \mathbf{S}_{(t)} < \mathbf{S}_{\max} \tag{8}$$

-Evaporation:

$$Loss_{(t)} = Ev_{(t)} \left(\frac{A_{(t)} + A_{(t+1)}}{2} \right)$$
(9)

-Precipitation:

$$\operatorname{Rein}_{(t)} = P_{(t)} \left(\frac{A_{(t)} + A_{(t+1)}}{2} \right)$$
(10)

-Releases:

$$\mathbf{R}_{(t)} > 0 \tag{11}$$

-Reversal equation of dynamic programming:

$$f_t(k) = Min[L_{klt} + f_{t+1}(l)]$$
(12)

In this equations, R(t), S(t), I(t), D(t), Loss(t), Rein(t) and A(t) are release, storage, inflow, demand, losses, precipitation and reservoir level, respectively.

By means of evaluation of ANN model and comparison with regression model, following cases were assumed.

In the first case, 60 periods from beginning of historical time series were selected and optimum release was calculated. 80 percent of these data was used for training the network and 20 percent remained data, which was selected randomly, was used for testing the model.

In the third case, all of the 480 monthly data was used for training the network and following method was used according to test the model.

Firstly, with mapping ARMA models to

historical series and selecting appropriated model (AR(1)), a monthly release data was used to solve DP model and results were used to test the ANN model.

In the forth case, the method was like third one with little difference. In this case 480 last release time series was used to solve DP model.

Reservoir storage at the first of each period and amount of demand in that period was used as input series of ANN model and outflow reservoir in that period was considered as output of ANN model.

All training process was done to reduce the amount of errors. In all cases, back propagation (MLP) was used as a solution. According to the best results for training the network, delta rule and sigmoid function were used as training rule and excitation, respectively. The number of hidden layers in each case is 1 or 2 and the number of neurons in each layer is between 1 and 4. in all cases, the number of hidden layers and neurons are selected corresponding to reduce RMS error.

Output results of ANN model and regression model is compared in figures 1, 3, 5 and 7 for test data. On the other hand, figures 2, 4, 6 and 8 show the distribution rate of forecasted data for both models` results.



Fig.1 Variation of monthly release with ANN and

Regression - First case



Fig.2 comparison of outputs of ANN and Regression models with real values – First case



Fig.3 Variation of monthly release with ANN and Regression – Second case



Fig.4 comparison of outputs of ANN and Regression models with real values – Second case



Fig.5 Variation of monthly release with ANN and Regression – Forth case





Fig.6 comparison of outputs of ANN and Regression models with real values- Forth case

As it can be seen, the results of both models are near to each other, and in some cases they can show a good approximation of considered case. But, gradually with the increasing in the rate of input data from case 1 to case 4, the difference between exact results (from DP model) and results of ANN model and regression model increases and correlation coefficient decrease.

Additionally, results of ANN model for cases 1 and 2 are better than regression model, while the results of regression model for cases 3 And 4 are better.

5 Conclusion

According to the simplicity of using ANN models and because of their fastness in general, the usage of this method was investigated in this paper. So in each month, by forecasting of inflow of reservoir in that period, demand of that month in down stream and the reservoir level in the same period, input data of ANN model is available and the release of that month can fit to the optimum value.

Achieving this purpose, 4 cases was investigated, and evaluation of results shows that using of this method for low periods of forecasting is reliable (in comparison with regression model), but with the increasing of number of periods, the accuracy is decreasing. So, considering following notes are unavoidable: 1- decreasing the number of forecasting periods and trying to retrain the network with accurate data. 2- Trying to provide a vast range of input data by producing various historical time series with dynamic programming that can enhance ANN model to be trained by every possible monthly release during operational period.

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