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Combining Stochastic Dynamic Programming (SDP) and Artificial Neural Networks (ANN) in Optimal Reservoir Operation

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Abstract*: After development of any optimization model a post-optimization simulation is needed for two purposes: 1) Checking and evaluating of system performance and 2) Computing performance criteria. The common rule is developing a simulation model in the form of a computer code. In this paper, using stochastic dynamic programming, the optimum operating rule of a hydropower system is derived. Then capability of artificial neural networks (ANNs) has assessed as a substitution of simulation model. The optimization model has divided to 50 classes of discrete storage volumes and 8 classes of inflows in each time period. Derived optimum rules then have applied for ANN model training. Then the optimum releases of a 43 year historical record has determined with simulation model and ANN model, as model testing. The results show that the optimum releases of reservoir in both ANN and simulation models are very close together.*

Key Words: *ANN, SDP, Optimal Reservoir operation.*

1. INTRODUCTION

Providing a simulation model after developing any optimization model will be necessary for: 1) Checking and evaluating the system performance and 2) Computing performance criteria. The obvious example of such a procedure can be seen in reservoirs operation problem. Usually dynamic programming (DP) will be used for driving the optimum operation policies (Belman, 1957). In such cases, after developing the operation policies of reservoirs, operating is calculated and then performance criteria such as reliability, resiliency and vulnerability are calculated (Hashimoto, et. al. 1982). This process is performed by some computer codes called "simulation models".

On the other hand, after some evaluations which mentioned, the simulation model benefits in real time operation of the system. Since the optimization model has the discrete variables (states and decisions), one of the other usage of such simulation models is in performing continues value of variables in the optimum conditions (optimum releases of reservoirs). In this paper the simulation model task is behalf of the artificial neural network (ANN) model. In the last decades, there have been some significant advances in the case of ANN, especially in the field of hydrology and the usage of those techniques is spreading everywhere. Preparing the train and test data is the first step in using the ANN models. Then the structure of an ANN model will be constructed defining: 1) the number of hidden layers and neurons in each layer. 2) Selection of transformation function type. Finally supposing the method for acquiring optimum weigh of the nodes, the final network will be implemented by trial and error.

In this study a SDP model is used for optimum operation policy of a hydropower reservoir and then a simulation model presents the optimum releases of the monthly reservoir in a period of 43 years. These two series of information represent the train and test data of the ANN models, respectively.

Since the SDP model rules are available for each month, the ANN models have been developed according to the SDP, and we have proposed 12 ANN models for every different month. The procedure is based on the 3 variables: S_t, Q_t, and R_t in each period. Where, S_t is the initial storage volume of reservoir in period t, Q_t inflow to reservoir and R_t is the optimum release of reservoir in period t. S_t and Q_t are state variables and forms the input data of ANN model which are discrete variables, and R_t, which includes of some discrete variables too, is the decision variable and output layer of ANN model.

Multilayer perceptron networks, sigmoid transformation function and back propagation algorithm (delta rule) for weight repairing process have been selected. For each month an independent network is obtained in different runs and controlling (minimizing) the errors in each run. It means that in each run, the number of hidden layer and numbers of neurons in each layer have been changed to achieve the best combination of them, which the errors are at least. Using the best network optimum historical monthly releases obtained from the ANN model compared with the same resulted from the simulation model.

The case study is the Karoon 5 hydropower dam in south west of IRAN, which is probably the last hydropower dam in the series of in Karoon River dams.

2. STOCHASTIC DYNAMIC PROGRAMING

Stochastic dynamic programming (SDP) is an optimization method which widely used in optimization of water resources systems (Loucks, et. al. 1981; yakowitz 1982; Mays and Tung 1992).

The form of the SDP model used in this paper was developed by Loucks et al. (1981). In this model, the inflow into the reservoir and the storage volume at the beginning of each period are the state variables. The release from reservoir or its equivalence, the storage volume at the end of the period is the decision variable. Considering that the model is of the discretized type. It is necessary to divide the inflow in each period into NI classes and the storage volume into NK classes. The continuity equation is as follows (Loucks et al., 1981),

$$R_{kilt} = S_{kt} + Q_{it} - E_{klt} - S_{l,t+1} \qquad [1]$$

In which R_{kilt} is the release in the period t, S_{kt} initial storage volume, $S_{l,t+1}$ final storage volume, E_{klt} reservoir evaporation volume, and Q_{it} is the inflow into the reservoir. k, l and i are the indexes of initial storage volume, final storage volume and inflow during the t^{th} period respectively. If $f_t^n(k, i)$ is the loss, for the whole system with n remained periods of operation, the recursive equation of the SDP backward model would be:

$$f_t^n(k,i) = \min\left[LS_{kilt} + \sum_j P_{ij}^t f_{t+1}^{n-1}(l,j) \right] \qquad [2]$$

In which LS_{kilt} represent the loss of the system in period t taking the above-mentioned state variables and P^t_{ij} is the transition probability of flow from period t to period t+1, in such way that flow in period t would be equal to Q_{it} and in period t+1 would be equal to $Q_{j,t+1}$. This probability is defined and calculated with the assumption that inflow in to the reservoir is in the form of a Markov chain. Solving the recursive equation in consecutive years, the optimized policy is obtained as R=R(k,i,t) or l=l(k,i,t). The former would present the optimum release and the later would present the optimum final storage volume. This policy is repeated in consecutive years as indication of reaching the optimal solution. More over, the steady state condition is reached when the sum of annual expected loss is independent of t, i and k indexes and is constant for all these indexes as:

$f_t^{n+T}(k,i) - f_t^{n}(k,i) = cte.$	[3]

In which T is the total number of within year periods. The optimum releases, obtained from the SDP model, is a function of initial storage volume, and inflow during the current period as:

$R_{opt}(t) = f\left(Q(t), S(t)\right)$	[4]

Consider reservoir of a dam with construction purposes of hydropower production. The hydropower production relations are:

$E_t^{tar} = PPC.PF_t.Hour_t$	[5]
$E_t = 2.725.H_t.R_t.e$	[6]
$E_t^{\max} = PPC.Hour_t$	[7]

In which E_t^{tar} is the Target energy in period t in MWHr ; PPC is the installed capacity of power plant in MW; PF_t is the plant factor of the powerplant in period t; $Hour_t$ is the total number of hours in period t; E_t is the total produced energy in period t in MWhr; H_t is the net head of turbine in period t in m, R_t is powerplant release in period t in MCM, e is the overal efficiency of powerplant, and E_t is the maximum productable energy in period t in MWhr.

The loss due the deviation of produced energy from target value could be obtained by:

$LFE_t = CE(E^{tar}_t - E_t)^{NE}$	[8]

In which LFE_t is the loss (penalty) of energy in period t, and CE and NE are coefficient and power of the energy loss function respectively.

3. ARTIFICIAL NEURAL NETWORKS

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 neural networks (Thirumalaiah and Deo, 1998), backpropagation in hydrological time series forecasting (Fuller and Lachtermacher,1994), performance of neural networks in daily stream flow forecasting (Birikundavyi et al.,2002), daily reservoir inflow forecasting using artificial neural networks with stopped training approach (Coulibaly et al.,2000), and finally comparative analysis of event-based rainfall-runoff modeling techniques-deterministic, statistical, and artificial neural networks (Jain and Indurthy, 2003).

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.

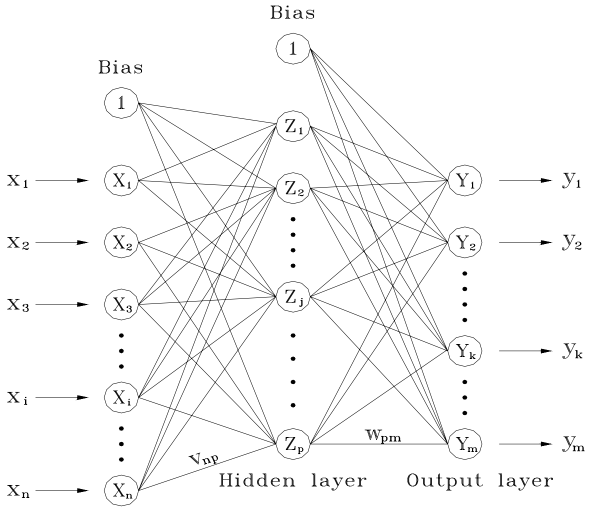

Figure 1. A typical neural network

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 **X** is received by each unit and weights leading to the node form a weight vector **W**. The inner product of **X** and **W** is net and the output of the node is **f** (net).

$$net = \mathbf{X}.\mathbf{W} = \sum x_i.w_i \qquad [9]$$

$$out = \boldsymbol{f}(net) \qquad [10]$$

f is called activation function whose functional form determines response of the node to the input signal it receives. Sigmoid function usually used in different applications, given as (9):

$$f(x) = \frac{1}{1+e^{-x}} \qquad [11]$$

Training of 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, and 3)Adjusting the weights in order to reduce the error. There are some learning rules based on Back Propagation algorithm in networks, and the most applicable one is Generalized Delta Rule. Weights are adjusted according to the following equation:

$$\Delta w_{ij}(n) = -\alpha.\frac{\partial E}{\partial w_{ij}} + \eta.\Delta w_{ij}(n-1) \qquad [12]$$

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 (12), α and η are learning rate and momentum, respectively; and they are both useful for a better training process.

Model validation is carried out to understand how a network is able to response to training set and to a new set to which the network hasn't faced to (testing set). Performance of a network is usually evaluated by some parameters, such as: 1-RMSE (Root Mean Square Error); 2-R (Correlation Coefficient); 3-e (Relative Error). All these parameters should be evaluated for both training and testing sets.

4. CASE STUDY: THE KAROON 5 DAM AND POWER PLANT

3.1. General Specification

Karoon River is the largest surface water resources of IRAN. For the moment, the dams Karoon 1 and Masjed Soleiman have been constructed on this river and the dams Upper Gotvand, Karoon3 and Karoon 4 are under construction. The dams Khersan, Bazoft and Karoon 5 at upstream parts of the river are also under study. At the upstream of these sites, Koohrang tunnels of 1 and 2 transfer part of the river water to the neighboring catchments. Figure 2 shows the location of under study region.

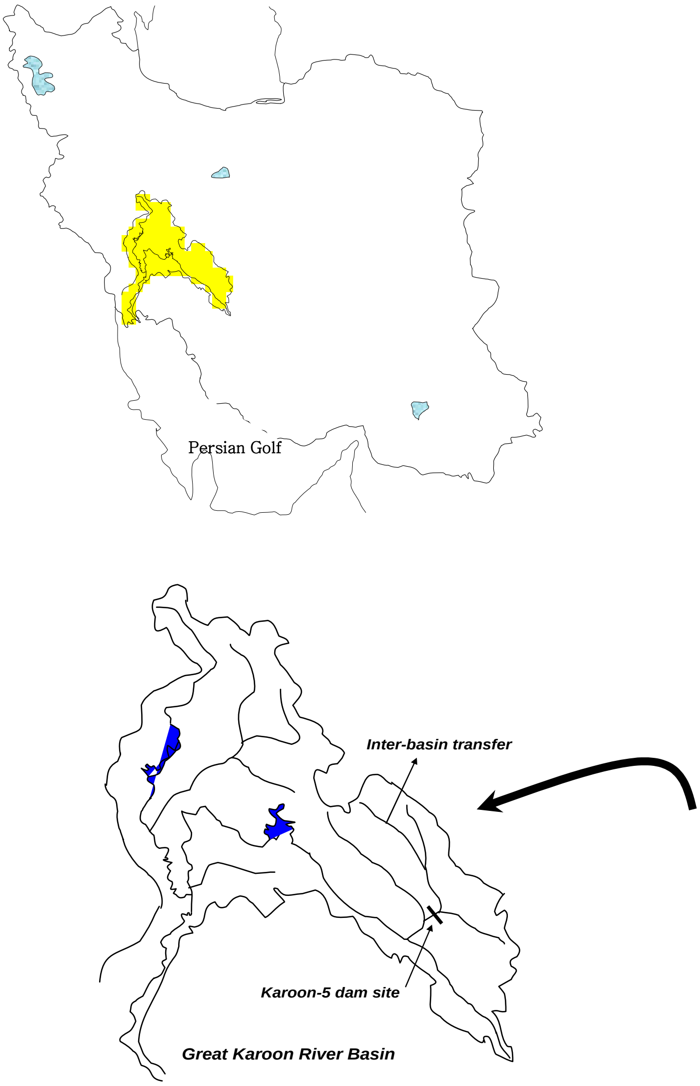

Figure 2. General layout of study area

The area of river basin at the dam location is 10186 Km^2 and the long-term average yield in natural situation (without diversion of water at the upstream parts) is about 114 m^3/s. Long term average annual precipitation of the watershed is about 613 mm. 35 m^3/s of the river yield is consumed at the upstream or is transferred to the other basins in the neighborhood. Consequently, the annual average inflow to the reservoir is about 78 m^3/s. In this study a 43 year time series of inflow (from 1956 to 1998) has been used. Based on the previous studies (Moshanir 2001), the power plant installed capacity, for plant factor of 25% and normal water level of 1200 masl with a dam height of 176m (from the river bed at the dam site), has been determines about 500 MW. Other required data also prepared based on those studies.

3.2. Optimum Operation Policy of Reservoir

The active storage of the reservoir is discreted into 50 classes and the monthly inflow to reservoir is discreted into 8 classes. Solving the SDP model, the optimum releases for each month is derived. Figures 3 and 4 demonstrate the typical optimum policy in each combination of inflow and storage volumes for May and Nov., respectively.

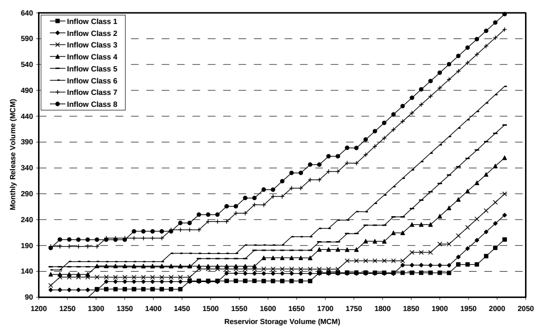

Figure 3. Optimum policy for reservoir operation in May

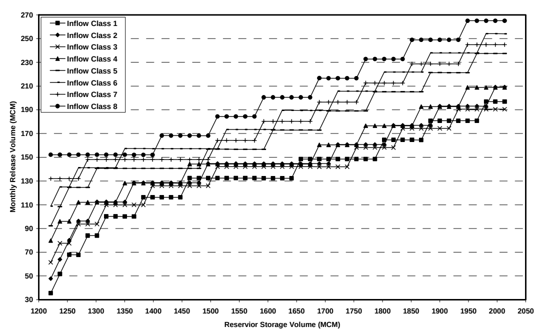

Figure 4. Optimum policy for reservoir operation in Nov

Using these rules, the monthly optimum releases of reservoir during a period of 43 years are calculated through a simulation model.

3.3. ANN Models

The process following to obtain the best networks for different months are the same as below:

Results of SDP model for each month which consist of 400 (50×8) data implement the input and output layer data of ANN model. The Q_t and S_t are input and R_t has the rules of output layer. Altering the number of hidden layer and changing the number of neurons in each layer and then checking the root mean square error (RMSE) of each case in every iterations, the best network will be chosen. The final structure of network for each month is presented in Table 1.

Table 1. The final structure for ANN networks in each month

Month	Oct	Nov	Sep	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Agu
Number of Neurons in Hidden Layer 1	8	10	20	6	2	5	20	10	10	23	15	34
Number of Neurons in Hidden Layer 2	8	7	15	0	1	3	20	8	11	12	9	29

Figures 5 and 6 show the typical regression between simulation and ANN output data in the case of train and test for May and Nov., respectively.

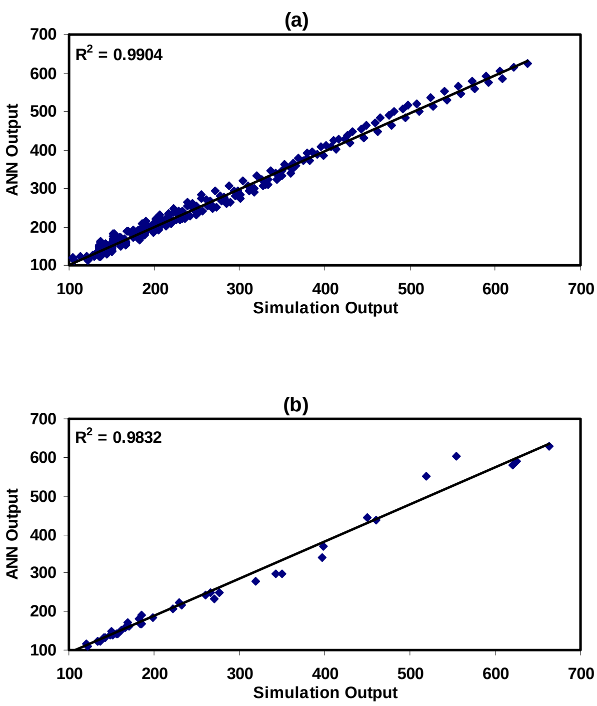

Figure 5. Regression between ANN and Simulation outputs for May (a) Training, (b) Testing

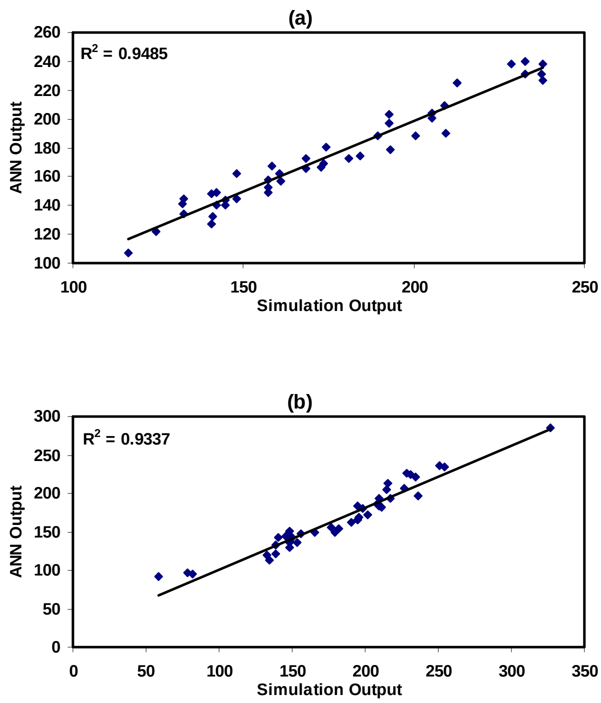

Figure 6. Regression between ANN and Simulation outputs for Nov (a) Training, (b) Testing

Then for evaluating the resulted networks, the monthly releases of the ANN model have been compared with those from the simulation model. Basic assumption is that the optimum releases taken from simulation model are the global optimum. As an example, Figures 7 and 8 illustrate the reservoir releases for May and Nov., respectively.

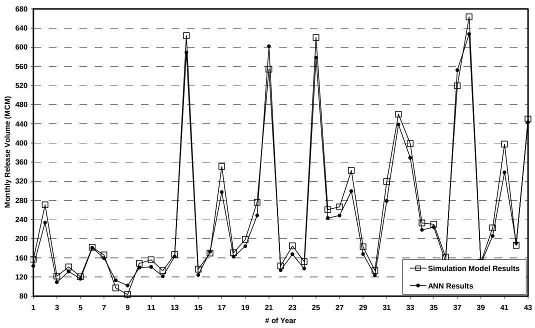

Figure 7. ANN and Simulation results for monthly release volume in May

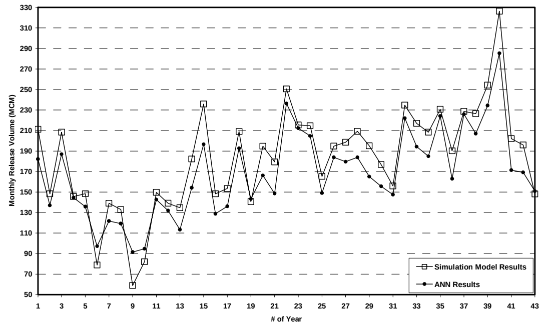

Figure 7. ANN and Simulation results for monthly release volume in Nov

As it can be seen the results obtained of both models are somehow similar. For further evaluation, the estimated relative errors (RE) for each month are calculated as below and are presented along with correlation coefficient in Table 2.

Table 2. R^2, RMS, and RE errors for train and test data in different months

Month		Oct	Nov	Sep	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Agu
R^2	Train	0.956	0.961	0.960	0.972	0.931	0.969	0.976	0.990	0.965	0.960	0.961	0.961
	Test	0.981	0.934	0.887	0.941	0.910	0.964	0.915	0.983	0.976	0.965	0.963	0.948
RMS	Train	0.020	0.014	0.017	0.012	0.019	0.022	0.012	0.011	0.012	0.015	0.017	0.018
	Test	0.022	0.016	0.022	0.016	0.014	0.023	0.022	0.020	0.014	0.016	0.016	0.026
RE	Train	4.559	4.773	4.862	4.316	6.692	6.016	6.945	4.811	4.674	3.687	3.479	3.483
	Test	3.060	10.90	5.983	10.94	10.84	7.834	10.23	7.658	7.670	7.182	4.180	3.542

$$RE = \left(\sum_{t=1}^{n} \left| \frac{R_t Sim - R_t ANN}{R_t Sim} \right| \right) / n \qquad [13]$$

Where, RE is the relative error, n is the number of years, and $R_t Sim$ and $R_t ANN$ are the monthly releases from Simulation model and ANN, respectively.

4. CONCLUSION

In this study the performance of ANN models in extracting the optimum operation policy of reservoirs, as a tool for substituting of simulation models is evaluated. For this reason and more, the Karoon 5 hydropower dam is considered. Using a SDP model, the discrete values of optimum releases for each month, which are a function of both monthly initial storage volumes and mean monthly inflow to reservoir in that month, will derive. The optimum monthly releases in a 43 years historical period are obtained by a simulation model using the SDP rules. These two parts of data were used in training and testing an ANN model and the results shows that ANNs are good substitutions to simulation models, and for the considered case study. In this paper, the resulted output from simulated and ANN models were very close together.

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