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Estimation of Storage of Sukhi Reservoir Using ANN Techniques

Daivakshi Shastri	Student of final year M.E WRM,Government Engineering College, Surat.
B. M.Vadher	Prof.and principle Civil Engineering Department,Government Engineering College, Surat.
Dr. S. M. Yadav	Prof. Civil Engineering Department, Sardar Vallabhbhai National Institute of Technology, Surat, Gujarat,India

ABSTRACT

Hydrologic forecasting plays an ever increasing role in water resource management, as engineers are required to make component forecasts of natural inflows to reservoirs for numerous purposes. Prediction for hydrologic events has always been an important issue for optimizing and planning the whole system. In this study, two different ANN (Artificial Neural Networks) techniques (Generalized Feed Forward network and Multilayer Perceptron) were used for Sukhi reservoir project. A total of 22 years of historical data were used to train and test the networks. To evaluate the accuracy of the proposed model, the Mean Squared Error (MSE) and the Correlation Coefficient (CC) were employed and found the network to be cross validated and trained properly for both models. The developed model shows good agreement with actual observation.

KEYWORDS: Artificial Neural Network (ANN), Storage, Generalized Feed Forward network, Multilaye

1. Introduction

Due to rapid growth of population and economies in the world, water is becoming a precious and scarce resource as result of grooving demands from various purposes, such as irrigation, hydropower, municipal, industrial and navigation supply etc. reservoir system is an important part of water resource management. Reservoirs are structures used for water conservation and supply throughout the world. Reservoir system has to min purposes; conservation and flood control. The purpose of conservation is to control and regulate water for hydropower, water supply, navigation, irrigation etc. the purpose of flood control is to reduce flooding throughout the retention of water during flood periods.

During both flood and drought situations, decision to open or close water gate is a critical action that need to be undertaken by dam operator as late decision will not only cause flood downstream but also will damage dam structure. Releasing the water earlier before the reservoir reaching its full Capacity might reduce the flood risk downstream. However, one cannot be sure that released water will be replaced and use during less intense rainfall. Researchers believe that the use of forecasting and warning system might improve the dam operation and decision. In practice, the water release or the gate opening decision depends on the operating rules. These rules are static and do not consider the dynamic nature of the hydrology systems. Therefore, non-structural approach such as forecasting is vital to support the water release or the gate opening decision.

Reservoir operation is a complex problem that involves many decision variables, multiple objectives as well as considerable risk and uncertainty In addition, the conflicting objectives lead to significant challenges for operators when making operational decisions. Traditionally, reservoir operation is based on heuristic procedures, embracing rule curves and subjective judgements by the operator. This provides general operation strategies for reservoir releases according to the current reservoir level, hydrological conditions, water demands and the time of the year. Applying optimisation techniques for reservoir operation is not a new idea. Various techniques have been applied in an attempt to improve the efficiency of reservoir(s) operation. These techniques include Linear Programming (LP); Nonlinear Programming (NLP); Dynamic Programming (DP); Stochastic Dynamic Programming (SDP); and Heuristic Programming such as Genetic algorithms, Shuffled Complex Evolution, Fuzzy logic, and Neural Networks etc. In reservoir operation, LP is well known as the most favoured optimisation technique with many advantages. It is easy to understand and does not require any initial solution.

Determination of the size of the structure is mainly based on the statistical data of the natural events that will affect the structure. For reservoir management purposes several methods are used. The main purpose is to optimize the water supply capacity of the designed structure. These methods are especially based on the continuity equation.

$$S(t-1) + Q(t) - E(t) - D(t) = S(t)$$

Where;
S = Storage of the reservoir
t = Time increment
Q = inflow to the reservoir
E = evaporation losses
D = discharge of reservoir.

At the stage of the planning optimization of the reservoir size is a very important subject. Before the construction of a dam a procedure is assigned for determining the optimum size of the reservoir. This procedure is called the operation study of a dam. In operation study the aim is to optimize the reservoir volume (that is storage) for abstracting sufficient amount of water from the dam reservoir. (Ismail KILINÇ, Kerem CIĞIZOĞLU).

The artificial neural networks are techniques that can model, map, and demonstrate the non linear relationship of complex phenomena. The artificial neural networks are universal and highly flexible function approximators, first used in the fields of cognitive science and engineering (Kaastra and Boyd, 1996). The artificial neural networks are widely used and have become increasingly popular in a broad range of fields. The neural networks are less sensitive to the error term assumptions and can tolerate noise, chaotic components, and heavy tails better than most other methods (Masters, 1993).

2. Artificial neural network

A neural network is a method that is inspired by the studies of the brain and nerve systems in biological organisms. Neural networks have the capability of self-learning and automatic abstracting. Applying this technique may reduce the time of modelling the complex systems. Artificial neural networks are important alternatives to the traditional methods of data analysis and modelling. The Artificial neural networks are divided into two periods. In the first period neural network is trained to represent the relationships and processes within the data. After the network is adequately trained, it is able to generalize relevant output for the set

of input data. This output is compared with observed data from the real life. This second period is called as testing period. The network is trained and tested on sufficiently large training and testing sets that are extracted from the historical time series.ANN is divided in three part input layer, hidden layer and output layer (Ismail KILINÇ, Kerem CIĞIZOĞLU).

In real life, the things people see, hear, and feel come into the brain and become the experiences in their memory. These experiences will tell them what to do better in the future when they are doing similar things. Like the human brain, the function of an ANN in engineering application is usually to learn the relationship between the inputs and outputs from a given set of data so that it can be used to predict future output values from new given input values (Kneale et al 2005).

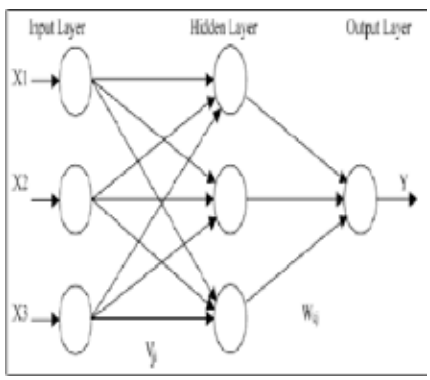


Fig.1 Basic structure of ANN

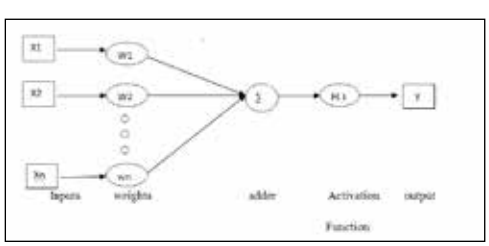
2.1 one- neuron model

A neuron is defined as information –processing unit that is fundamental to the operation of a neural network. Fig shows a simple one-neuron model to illustrate the neural network structure. There are three basic elements in a neural network model given as follows:

A set of connecting links, 'w' it is characterized by weight. The weights on the connections from the input x1,x2,....,xn to the neuron Y are w1,w2,...,wn respectively.
An adder,' Σ' for summing the weighting input signals.
V= W1X1+W2X2 +....+WnXn

An activation function, f(.), for limiting the amplitude of the output of a neuron. The output from the neuron model can be described by

Y=f(v)



There are several types of activation functions. Example of activation functions are given below:

Linear function:
F(v)=v
Non-linear sigmoid function:

Where 'a'is the slope parameter. (Wenrui Huanga,*, Simon Foo (2001))

There are many examples of applications of Artificial Neural Networks in the hydrological forecasting context. Recent experiments have reported that Artificial Neural Networks may offer a promising alternative for rainfall–runoff modelling (Hsu et al. 1995; Shamseldin 1997; Cigizoglu and Alp 2004, Anctil et al. 2004), stream flow prediction (Thirumalaiah and Deo 1998; Zealand et al. 1999; Campolo et al. 1999; Kisi 2004), reservoir inflow forecasting (Coulibaly et al., 1998; Jain et al., 1999) and suspended sediment estimation (Jain, 2001;Cigizoglu and Kişi, 2005). Coulibaly et al. (1999) reviewed the ANN-based modelling in hydrology over the last years, and reported that about 90% of the experiments extensively make use of the multi-layer feed-forward neural networks (FNN) trained by the standard back propagation (BP) algorithm (Rumelhart et al. 1986).

The performance of FFBP (Feed Forward Back Propagation) was found superior to conventional statistical and stochastic methods in continuous flow series forecasting (Brikundavyi et al. 2002; Cigizoglu 2003a; Jain and Indurthy 2003; Kisi 2004). In the majority of ANN applications in water resources the back propagation gradient descent algorithm is employed. This algorithm, however, requires a long training duration to obtain the desired error percentage.

2.2 Generalized feed forward network

Generalized feed forward networks are a generalization of the MLP such that connections can jump over one or more layers. In theory, a MLP can solve any problem that a generalized feed forward network can solve. In practice, however, generalized feed forward networks often solve the problem much more efficiently. A classic example of this is the two spiral problem. Without describing the problem, it suffices to say that a standard MLP requires hundreds of times more training epochs than the generalized feed forward network containing the same number of processing elements.

2.3 Multilayer Perceptron network

Multilayer perceptrons (MLPs) are layered feed forward networks typically trained with static back propagation. These networks have found their way into countless applications requiring static pattern classification. Their main advantage is that they are easy to use, and that they can approximate any input/output map. The key disadvantages are that they train slowly, and require lots of training data (typically three times more training samples than network weights).

3. Study area and data used

In this study the data from the Sukhi Dam was used. Sukhi Reservoir Project situated near village Sagdhra about 15.00 Km from Pavijetpur city of District Vadodara is located across river Sukhi & Bharaj of Narmada basin is the present study area. The project is meant for recharge/Irrigation.

River	Sukhi
Place	Vadodara district
Type of dam	Earth and masonry
Gross storage capacity	178.47 Mm3
Maximum height	38 m
Mean annual rainfall	1053 mm
Area of catchment	412 km2
Mean annual rainfall in the catchment	217.10 Mm3

Table No1 Some characteristics of Sukhi dam

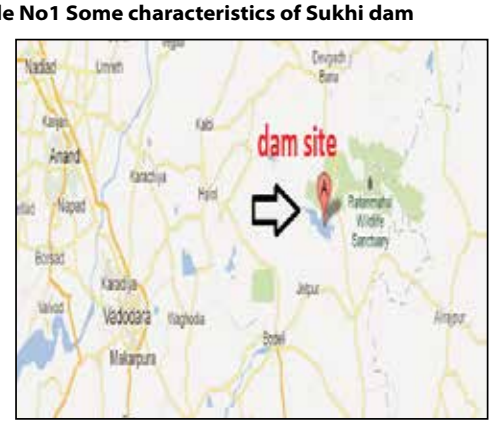


Fig .2 Location map of Sukhi dam

4. Model development

The model was developed using a back propagation algorithm of ANN and its ability to forecast the monthly reservoir was tested using 22 years of historical data of Sukhi reservoir project, Vadodra, Gujarat.

The historical data for the ANN modelling is divided into two sets called the training and the testing set.

The training set is the major part of the data that is used for training of the neural network for finding the governed pattern of data. The testing patterns are used for evaluating accuracy of the ANN trained model. Several patterns of input data have been employed to develop the optimum ANN model for the hydropower reservoir inflow. One hidden layer is designed for all the networks and each network was trained under several structures with different number of neurons in the hidden layer.

Model 1: The model is developed using monthly data where in one depended variable i.e. reservoir storage capacity at the end of t period and six independent parameters inflow, evaporation losses, discharge from left bank command area, right bank command area and spill over quantity with Generalized feed forward network of ANN.

Model 2:

The model is developed using monthly data where in one depended variable i.e. reservoir storage capacity at the end of t period and six independent parameters inflow, evaporation losses, discharge from left bank command area, right bank command area and spill over quantity with Multilayer perceptron network of ANN.

5. Results and discussion

The most important part of ANN model is its ability to forecast future events. The MSE and CC(R) criterions are employed for evaluation of the accuracy of both training and testing procedure. The best model is chosen according to the minimum MSE and the Maximum CC(R).

MODEL 1: MONTHLY DATA RESULTS

Fig 3 shows that the values of desired output and actual output are nearer to each other, so that the value of "r" is nearer to 1.0 and hence the obtained result for testing period is acceptable.

Table No 2

Input layer cell	Output layer cell	Number of training data	Number of testing data	Mean square error	Co relation co-efficient (R)
S(t-1)	S(t)	152	62	0.00056	0.999
E(t)					
RBMC(t)					
LBMC(t)					
I(t)					
SW(t)					

Where,
S (t-1) = storage at the beginning period
E (t) = evaporation losses I (t) = inflow
RBMC (t) = right bank main canal SW (t) = spillway discharge
LBMC (t) = left bank main canal

A graph for testing period of model creation is shown below it will give the comparison of actual data of output parameters versus output data by network.

Performance	at the end
MSE	7.132245952
NMSE	0.00227031
MAE	2.150261652
Min Abs Error	0.09919146
Max Abs Error	6.674181152
r	0.999002173

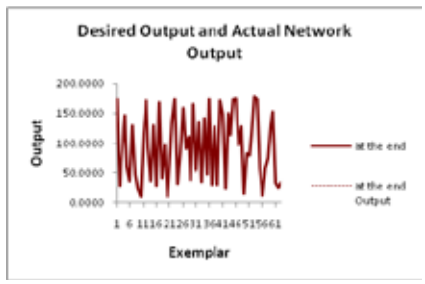


Fig .3 Actual vs. Desired

Result of testing period is shown in table and the value of "r" is 0.99 hence it can be concluded that the network is cross-validated and network is trained properly. If value of "r" comes closer to 1.0,

the model has good performance and it will predict result with accuracy.Values of "r", MAE and other parameters during training period of network are shown in table and they are acceptable.

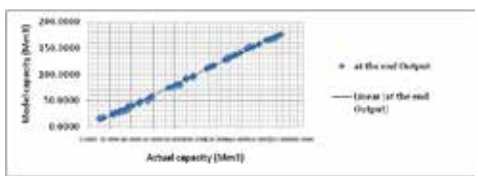


Fig 4 Actual output vs. Model output

MODEL 2: MONTHLY DATA RESULTS

Fig 5 shows that the values of desired output and actual output are nearer to each other, so that the value of "r" is nearer to 1.0 and hence the obtained result for testing period is acceptable.

Table No 3

Input layer cell	Output layer cell	Number of training data	Number of testing data	Mean square error	Co relation co-efficient (R)
S(t-1)	S(t)	152	62	0.00037	0.967
E(t)					
RBMC(t)					
LBMC(t)					
I(t)					
SW(t)					

Where,
S (t-1) = storage at the beginning period
E (t) = evaporation losses I (t) = inflow
RBMC (t) = right bank main canal SW (t) = spillway discharge
LBMC (t) = left bank main canal
A graph for testing period of model creation is shown below it will give the comparison of actual data of output parameters versus output data by network.

Performance	Capacity At the end 0f the peir0d (Mm3)
MSE	13.43172682
NMSE	0.006568001
MAE	2.995509506
Min Abs Error	0.036215319
Max Abs Error	9.063975313
r	0.967213059

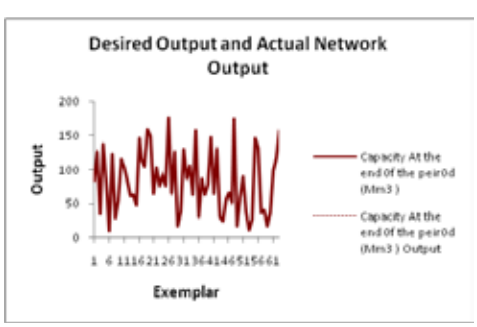


Fig .5 Actual vs. Desired

Result of testing period is shown in table no and the value of "r" is 0.96 hence it can be concluded that the network is cross-validated and network is trained properly. If value of "r" comes closer to 1.0, the model has good performance and it will predict result with accuracy.Values of "r", MAE and other parameters during training period of network are shown in table and they are acceptable.

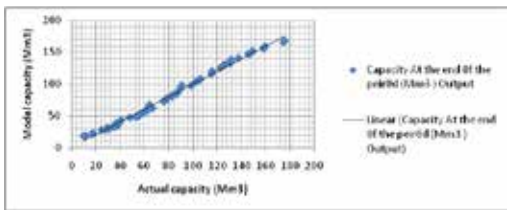


Fig6Actuaoutputvs.Modeloutput

6. Conclusion

The reservoir storage so obtained will helpful in

1. Determining mimimum and maximum storage in the reservoir for given demand
2. Help in maintaning water level (storage) in the reservoir as per monthly demand.
3. The devloped model will also help in flood control as it predicts storage after dedcting outgoing from the dam.

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