Forecasting Catchment Flow for a Coastal Lake Using Artificial Neural Networks

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ABSTRACT

Forecasting inflow to a lake from its surrounding catchments is essential for its regulation strategies. The prediction modeling of this inflow is difficult since it is an apparent non-linear and complicated hydrological phenomenon. Artificial Neural Networks (ANN) is emerging as a promising technique for modeling these types of complex water resources problems. ANN is a machine learning technique with flexible mathematical structure, which is capable of identifying complex non-linear relationships between input and output data without physical insight of the problem. In this study, the applicability of ANN for inflow forecasting to a salty lake known as Flat bay is investigated. This lake is situated on the northern side of Port Blair in Andaman and Nicobar Islands, India. Algorithms of two types of ANN architectures (1-5-1 and 2-5-1) are formulated, and are applied to a surrounding catchment named, Chouldhari, that feed water into the lake. A three layer feed forward ANN model with log sigmoidal activation function and trained by back propagation algorithm is used for this study. A comparative analysis based on standard statistical measures is performed for these two ANN architectures to evaluate their performance. The formulated ANN architecture for the lake provides an efficient tool for inflow forecasting and proper lake management.

Key words: Lake inflow forecasting, ANN model, Flat bay, Lake catchment management

INTRODUCTION

There are many practical situations where the main concern is making accurate predictions. In such cases, it is preferred to identify a direct mapping between the inputs and outputs without detailed consideration of the internal structure of the physical processes. The involvement of many often-interrelated physiographic and climatic factors makes the hydrological process not only very complex to understand but also extremely difficult to model, more so in case of a catchment flow exhibiting both temporal and spatial variability (Zhang and Govindaraju, 2000). The application of artificial neural networks (ANN) for rainfall-runoff modeling have added a new dimension to the system theoretic modeling approach. It has been applied in recent years as a successful tool to solve various problems concerned with hydrology and water resources engineering (Tawfic et al. 1997).

Artificial neural networks have been used by researchers for rainfall-runoff modeling, catchment flow prediction, ground-water modeling, water quality modeling, water management, precipitation forecasting, reservoir operations and other hydrological applications with acceptable accuracy (ASCE, 2000b). The availability of extended records of rainfall and other climatic data, which could be used to predict stream flow data, initiated the practice of catchment flow modeling (Lorrai and Sechi, 1995). The work by Karunanithi et al. (1994) has demonstrated the capability of ANN in stream flow forecasting. They observed that ANN have performed much better than the conventional models. Smith and Eli (1995) used the back-propagation artificial neural network model to predict peak discharge and time to peak by using simulated data from a synthetic catchment. Shamseldin (1997) used the conjugate gradient method to train the network using data from six catchments from different climates. Campolo et al. (1999) made use of distributed rainfall data, observed at different rain gauge stations for the prediction of water levels at the catchment outlet. Results of this model were very poor when only rainfall observations were used as the input. The model accuracies were found to improve when the water levels observed in the recent past were also used as input. Sajikumar and Thandaveswara (1999) used a temporal back-propagation neural network logarithm for monthly rainfall-runoff modeling in scarce data conditions. Many standard statistical measures were employed by Jain and Srinivasulu (2004) to assess the rainfall-runoff models.

In the identification of nonlinear processes, ANN should not be considered as a mere black box. A better understanding of the hydrologic system enables successful application of ANN. For instance, physical insight into the problem being studied can lead to a better choice of input variables for proper mapping. This will help in avoiding loss of information that may result if key input variables are
omitted, and also prevent inclusion of spurious inputs that tend to confuse the training process. A sensitivity analysis is performed in this study to determine the optimal architecture by including three types of input data set. The input variables that do not have a significant effect on the performance of ANN architecture can be trimmed from the input vector, resulting in a more compact network. The objective of the study is to formulate an optimum artificial neural networks architecture model for projecting the inflows to a natural bay or reservoir for its regulation strategies.

STUDY AREA

The area selected for the present study is the Flat bay, which is being considered for the development of a fresh water lake by the Government of India. The lake is situated on the northern side of Port Blair, capital city of Union Territory of Andaman and Nicobar Islands, India. Location and drainage area of the lake are shown in Figure 1. Andaman and Nicobar Islands consists of approximately 500 islands and are located at latitudes 6° N to 14° N and longitudes 92° E to 94° E in the Bay of Bengal. They have prominent topographical features with reserve forests, numerous creeks and bays. In recent times, the islands have acquired immense importance due to their strategic location, natural resources and tourism.

The Flat Bay lies between latitudes 11°36’37” N to 11°39’19” N and longitudes 92°39’47” E to 92°42’26” E with total drainage area of about 50 km². Highlands and hillocks slopping towards the Bay surround the lake. The approximate high and low water areas of the Flat Bay are 12.5 mm², 4.25 mm² (WAPCOS 1999).

METHODOLOGY

Artificial neural networks are composed of a set of layered processing elements called neurons. The first layer is called the input layer, the last layer is called the output layer, and the layers in between are called the hidden layers. The neurons at each layer are connected to the neurons in the subsequent layer through weighted interconnections. The net input to each neuron is converted to an activated value through weighted interconnections. The net input to each neuron is converted to an activated value through the activated function and is compared with the threshold value; bias, to generate the output of each neuron (Tawfic et al. 1997). An optimal architecture is considered the one yielding the best performance in terms of its efficiency and effectiveness measured by standard statistical parameters. No unified theory exists for determination of such an optimal ANN architecture, and thus is achieved through computational simulations. The number of nodes for input layer is equal to number of input vectors, and the output layer has only one node each corresponding to the number of variables to be predicted. The flexibility lies in selecting the number of hidden layers and in assigning the number of nodes to each of these layers. A trial-and-error procedure is generally applied to decide on the optimal architecture (ASCE, 2000a).

The study carried out by Minns and Hall (1996) points out the importance of standardization of the data. The pattern used to train the network is normalized, as the output range of the log sigmoid transfer unit is 0 to 1. In this model, all the values are divided by a number that is larger than the largest value presented in the data for pattern normalization.

Back-propagation is the most popular algorithm for training ANN (ASCE, 2000a). Each input pattern of the training data set is passed through the network from the input layer to the output layer. The network output is compared with the desired target output, and an error is computed. This error is propagated backward through the network to each node. The back-propagation algorithm involves two steps. The first step is a forward pass, in which the effect of the input is passed forward through the network to reach the output layer. After the error is computed, a second step starts backward through the network. For training, the error tolerance, momentum coefficient and learning rate parameters were assigned as 0.001, 0.001 and 0.01, respectively to activate the network.

The performance of an ANN is evaluated on the basis of the root mean square error (RMSE), coefficient of correlation (R) and average absolute relative error (AARE). RMSE, used to quantify the efficiency of the model architecture, is defined according to the following equation (Sinha and MacKim, 2000):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (T_{out} - A_{out})^2}{N}} \quad (1)$$

where $T_{out}$ = target output; $A_{out}$ = actual output; and $N$ = number of observations.

The correlation coefficient is a measure of the strength of the relationship between the calculated and observed values and is computed as follows (Keshari, 1996):

$$R = \frac{N \sum T_{out} A_{out} - \sum T_{out} \sum A_{out}}{\sqrt{\left[ N \sum T_{out}^2 - (\sum T_{out})^2 \right]} \sqrt{\left[ N \sum A_{out}^2 - (\sum A_{out})^2 \right]}}$$

The effectiveness of the model architectures in terms of their ability to accurately predict the data is evaluated by AARE statistics (Jain and Indurthy, 2003).
The mean monthly evaporation and rainfall data over the study area for a period of five years from 1981 to 1985 are used. These data are based on measurements taken for Chouldhari catchment.

\[
AARE = \frac{1}{N} \sum_{i=1}^{N} \left( \frac{T_{\text{out}} - A_{\text{out}}}{A_{\text{out}}} \right) \times 100
\]  

Table 1: Model performance evaluation for Chouldhari catchment

<table>
<thead>
<tr>
<th>S. No.</th>
<th>Architecture</th>
<th>RMSE</th>
<th>R</th>
<th>AA RE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1-5-1</td>
<td>6.27e-05</td>
<td>0.9986</td>
<td>8.34</td>
</tr>
<tr>
<td>2</td>
<td>2-5-1</td>
<td>6.49e-05</td>
<td>0.9974</td>
<td>8.35</td>
</tr>
</tbody>
</table>
RESULTS AND DISCUSSIONS

Two model architectures are developed to investigate the capabilities of ANN for forecasting inflow to the Flat bay. In the first 1-5-1 ANN architecture, only rainfall data are used for the input layer, thus the three layers consist of an input layer with one node, one hidden layer and an output layer with one node. In the second 2-5-1 ANN architecture, two inputs are considered for the input layer. For this case, evaporation rate is added as an additional input. The output in both of these cases has been taken as the runoff. The hidden layer is taken with five neurons. The number of hidden layers and neurons in the hidden layer are selected based on trial and error and available literature, as there is no standardized guideline available for it. The data for a period of 1981-1985 are divided into two data length: (i) monthly data set of 1981 to 1982 was taken for training, and (ii) monthly data set of 1983 to 1985 was selected for testing purpose.

Figures 2-5 show the results obtained from two model architectures for the Chouldhari catchment. It is evident from these figures that both architectures are able to simulate the runoff very accurately. However, the first 1-5-1 model architecture appears to be more appropriate than the second one, as it is giving better performance even the data is limited. Thus, the designed ANN architecture is able to recognize the patterns with limited training data. This is a very useful finding for the ungauged catchment. Such observation may be attributed to smaller watershed. In case of a larger catchment, more data may be required for training, especially having land surface heterogeneity of appreciable extent. Table 2 shows the values of RMSE, R and AARE for these two architectures of the ANN model for the Chouldhari catchment.

![Figure 2](image1.png)  
Figure 2 Target and output of model 1-5-1 for Chouldhari catchment

![Figure 3](image2.png)  
Figure 3 Error signal of 1-5-1 model for Chouldhari catchment
CONCLUSIONS

A simple ANN model is formulated for lake inflow forecasting and implemented to a bay located in Andaman & Nicobar Islands, India. Two architectures of the ANN are evaluated to find the optimum architecture model for predicting inflows from the drainage basin to the bay. The model is applied to a surrounding catchment named, Chouldhari which drains water to the bay. Results obtained reveal that both 1-5-1 and 2-5-1 ANN architectures with log sigmoid transfer function are capable of forecasting inflow into the bay perfectly. However, 1-5-1 is the optimal architecture, which yields the best performance in terms of standard statistical measures, while retaining a simple and compact structure. The formulated ANN architecture for the considered coastal water body provides an efficient tool for inflow forecasting and proper lake management.

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