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Artificial Neural Network based Runoff Prediction Model for a Reservoir

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Abstract

In recent years research on Artificial Neural Networks (ANN) proved to be most convenient and easy tool for modeling and analysis of non-linear events. This ability of ANN to model non-linear events is important in hydrology to model various hydrological events which are dominantly non-linear in nature. It is also capable of Modelling Non-linear relationship between Rainfall and Runoff as compared to other Mathematical modeling techniques. In this paper, ANN modeling is done with the help of MATLAB for prediction of water arriving at reservoir. Back Propagation (BP) algorithm is used to evaluate error and back propagate it for more accurate training of ANN.

1. Introduction

Rainfall-Runoff (RR) prediction is one of the most complicated processes in environmental modeling. This is due to the spatial and temporal variability of topographical characteristics, rainfall patterns, and the number of parameters to be derived during the calibration. Accurate RR predictions largely depend on the long-term observation and recordings of precipitation and runoff. Hydrological cycle is a highly nonlinear system, and it makes hydrological modeling very complicated. Rainfall-Runoff modeling plays an important role in flood control, water resources and water environment management. Modeling of such non-linearity and uncertainty associated with rainfall-runoff process has lot of importance. An ANN (Artificial Neural Network) may be treated as a universal approximator since it is capable to learn and generalize ‘‘knowledge or data’’ from sufficient data pairs. This makes ANN a powerful tool to solve large-scale complex problems such as pattern recognition, nonlinear modeling, classification, association, control, hydrology and many other. ANN models are well suited for hydrological time series modeling since they can approximate virtually any measurable functions upto an arbitrary degree of accuracy. Therefore they are increasingly being applied in daily runoff forecasting. ANN is expert at mapping non-linear relationship between inputs and outputs. Thus daily runoff forecasting based on artificial Neural Network (ANN) models has become quite important for effective planning and management of water resources. ANN models perform better than Process-based models. Several studies indicate that ANN have proven to be potentially useful tools in hydrological modeling such as for modeling of rainfall-runoff processes, flow prediction, water quality predictions, operation of reservoir system, groundwater reclamation problems etc. The objective of the present study is to develop rainfall-runoff models using ANN methods.

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2.Literature Review

Artificial Intelligence(AI) has been popular since 1990s and has been widely used in many areas. In 1890, William James published the first work about brain activity patterns. In 1943, McCulloch and Pitts produced a model of the neuron that is still used today in artificial neural networking. In 1949, Donald Hebb published ―’The Organization of Behavior’, which outlined a law for synaptic neuron learning. This law, later known as “Hebbian Learning” in

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honor of Donald Hebb, which is one of the simplest and most straight-forward learning rule for artificial neural networks. In 1951, Marvin Minsky created the first ANN while working at Princeton. In 1958 —'The Computer and the Brain' was published, a year after John von Neumann's death. In that book, von Neumann proposed many radical changes to the way in which researchers had been modeling the brain.

Back-propagation neural network (BPNN) is the most popular neuron network, which can applied in rainfall-runoff modeling successfully. BPNN technique has the capability to model various characteristics of hydrologic resources system, including randomness, fuzziness, non-linearity, etc. BPNN is usually used for function approximation through training a network by input vector and corresponding output vector. A BPNN consists of input layer, hidden layer and output layer, and it propagates backward the error at the output layer to the input layer through the hidden layer to decrease global error.

3. Proposed System Architecture

This paper includes an Artificial Neural Networks (ANN) with Back propagation for Modelling of Hydroligical event. ANN is a parallel distributed processing system made up of highly interconnected neural computing elements. Fig.1 shows System Architecture.

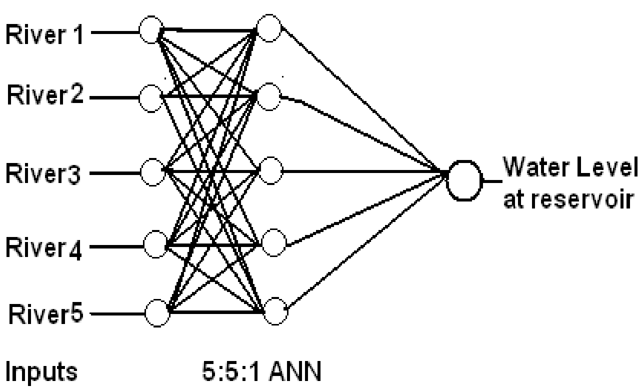

Fig.1. ANN with Back-Propagation

As shown in above, System mainly consists of 5:5:1 ANN. Here ANN consists of three layers: the input layers, where the data are introduced to the network; one or more hidden layers, where the data are processed and the output layer, where the results for given inputs are produced. ANN consists of many nodes, which are processing units called neurons. These Neurons, processes the information. The signals are transmitted by means of connecting links. The links posses an associated weights, which are multiplied along with the incoming signal (Net Input).Output Signal is obtained by applying activation functions to the net input. Various learning mechanisms exist to enable the ANN to acquire knowledge.

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Each layer is made up of several nodes, and layers are interconnected by sets of correlation weights. Each input node unit (i=1,…,m) in input layer broadcasts the input signal to the hidden layer. Each hidden node (j=1,…,n) sums its weighted input signals according to

$$Z_{\_inj} = b_j + x_i W_{ij}$$

applies its activation function to compute its output signal from the input data as

$$Z_j = f\,(Z_{\_inj})$$

and sends this signal to all units in the hidden layer. Where wij is the weight between input layer and hidden layer, b_j is the weight for the bias and x_i is the input signal.

The net of a neuron is passed through an activation or transfer function to produce its result.Therefore, continuous-transfer functions are desirable. The transfer function, denoted by f(k), defines the output of a neuron in terms of the activity level at its input. There are several commonly used activation functions defined as

- *The Identity function*
- *The Binary Step function*
- *The Binary Sigmoid (Logistic) function*
- *The Binary Sigmoid (Hyperbolic Tangent) function*

The transfer function used in the present report is sigmoidal which is continuous, differentiable, monotonically increasing function, and it is the most commonly used in the backpropagation networks. The output is always bounded between 0 and 1, and the input data have been normalized to a range between 0 to 1. The Slope a is taken assumed to be 1.The sigmoid activation function will process the signal that passes from each node by

$$f(Z_{inj}) = 1 / (1+ e^{-Zinj})$$

Then from second layer the signal is transmitted to third layer. The error information is transfer from the output layer back to early layers. This is known as the back propagation of the output error to the input nodes to correct the weights.

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3.1. Learning Processes

By learning rule we mean a procedure for modifying the weights and biases of a network. The purpose of learning rule is to train the network to perform some task. They fall into three broad categories:

- *Supervised learning*
- *Reinforcement learning*
- *Unsupervised learning*

In this proposed system supervised learning process is being used.This learning rule is provided with a set of training data of proper network behavior. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.

3.2. Training of an ANNs

A neural network has to be configured such that the application of a set of inputs produces the desired set of outputs. Various methods to set the strengths of the connections exist. One way is to set the weights explicitly, using a priori knowledge. Another way is to 'train' the neural network by feeding it teaching patterns and letting it change its weights according to some learning rule.

3.3 Back Propagation

Multi-layer feed-forward network can overcome many restrictions compared to single layer network. But still there is problem of how to adjust the weights from input to hidden units. An answer to this question is that the errors for the units of the hidden layer are determined by back-propagating the errors of the units of the output layer. And hence this method is often called the back-propagation learning rule. Back-propagation can also be considered as a generalization of the delta rule for non-linear activation functions and multilayer networks. Backpropagation is the most commonly used supervised training algorithm in the multilayer feed-forward networks. The network weights are modified by minimizing the error between a target and computed outputs. The weights are updated continuously until minimum error is achieved. A training pair is selected from the training set and applied to the network. The network calculates the output based on the inputs provided in this training pair. The resultant outputs from the network are then compared with the expected outputs identified by the training pair. The weights and biases of each neuron are then adjusted by a factor based on the derivative of the sigmoid function, the differences between the expected network outputs and the actual outputs (the error), and the actual neuron outputs. Through these adjustments it is possible to improve the results that the network generates, and thus the network is seen to *learn*. How much each neuron's weights and bias are adjusted in the back-propagation algorithm also depends on a *learning parameter*—which is nothing but the *learning Rate(α)* and it is a single factor by which all adjustments are multiplied. A large learning rate can result in training oscillatation from one poor extreme result to another, whereas a small learning rate can lead to a situation where the network does not learn anything and is caught in a local minimum, unable to reach a more accurate set of weights. So proper selection of learning rate is most important before training the ANN.

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3.3.1.Procedure for Back-Propagation of Error

Back propagation error can be calculated as,

Error $e_k = (t_k - y_k) f(y_{-ink})$

Where e_k-error information,

t_k-output target unit k,

y_k-output unit k

3.3.2.Weight and Biases Updation

Each output unit (y_k) updates its bias and weight to minimize error between output and target.

1.The Weight Correction is given by,

$\Delta W_{jk} = \alpha e_k Z_j$

Where α is learning rate

Thus $W(new) = W_{jk}(old) + \Delta W_{jk}$

2. Biase Correction is Given by,

$\Delta b_{ok} = \alpha e_k$

Thus $b_{ok}(new) = b_{ok}(old) + \Delta b_{ok}$

4.Conclusion and Future Work

In this paper, research on ANN is being carried out for Hydrological Model to Predict water level at Dam. Back Propagation learning rule is being used to optimise error by evaluating and back propagating error for more accuracy in training. After successful training of this ANN model, the results can be used to control Reservoir operations such as flood controlling, Water usage management,etc

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