Flood Forecasting Using Neural Networks

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Abstract. This paper deals with flood routing in rivers using neural networks. The unsteady river flow may be formulated in terms of two one-dimensional partial differential equations. These are the Saint Venant flow continuity and dynamic equations.
Several methods of solution of these equations are known. These methods are based upon characteristics of equations, finite difference, finite element and finite volume. All of these methods have some limitations regarding data requirements and complications involved in solution of equations. Neural network techniques have been developed recently. These are easy to use and need comparatively less data and less labor for solution of the problem. One of these techniques is used in this research work. The model was applied for flood routing in River Chenab in Pakistan. Its reach from Marala to Khanki was selected. Date for various flood events was collected from Meteorological Department, Lahore and Flood Commission Islamabad. The error between the observed and simulated values of flood hydrograph ordinates was found to be in acceptable range.

1 Introduction

Rivers, which provide water to the millions of people settled on their banks and flood plains, can also bring calamity in the form of floods. Today, all over the world, hundreds of floods occur annually. The consequences of these floods are the persistent recurrence of damage and tragedy of death and disease, and a constant menace to the progress of industry and civilization.

The climatic conditions of Pakistan are hot rainy in summers and dry cold in winters. There are five large rivers, which are in flood during the monsoon season. These floods are devastating. For example, during 1988 and 1992, the floods caused widespread human sufferings, loss of lives and colossal damage of private and public infrastructure. In 1988, flood resulted in the loss of 370 people and damaged more than one million hectare of agricultural land. In 1992, flood caused even greater damage, more than 1000 people died and about 13000 villages with about one million houses were destroyed. Over two million hectares of agricultural land inundated resulting in the loss of about 15 percent of both cotton and rice crop. The nation wide damage was estimated at about $ 2.2 billion (Khan R.A., 2001).

In order to safeguard property and lives, flood control and its dissipation play an important and vital role. Flood forecasting becomes utmost important in such

Ghumman A., Ghani U. and Shamim M. (2004).
Flood Forecasting Using Neural Networks.
In *Proceedings of the First International Workshop on Artificial Neural Networks: Data Preparation Techniques and Application Development*, pages 9-15
DOI: 10.5220/0001148800090015

conditions. Flood routing techniques have been developed mainly for the study of floods traveling through channels, reservoirs and lakes. The technique determines the time and magnitude of flood peaks occurring at various points along a river as the flood travels downstream. Presently, flood routing is employed for a wide variety of problems associated with water use. Some of these include; (i) evaluating past floods for which records are incomplete; (ii) determining hydrograph of channel flow from hypothetical design floods on tributaries and upstream reaches of the main channels: (iii) forecasting floods along the main course of a river, by use of predicted hydrographs at key points in the drainage network; (iv) determining hydrographs modified by reservoir storage; and (v) studying the effects of water resources development on the downstream flow conditions.

Flood routing is carried out by solving the unsteady flow equations. These are partial differential equations and for solution of these equations, many simplifying assumptions such as uniform roughness, constant channel cross-section with constant bed slope etc., are made. Without these assumptions, the relationship between variables becomes more complex and the method of solution needs more data to describe the channel and wave conditions. Faced with the limitations of time and economy in the preparation of data, one has to resort to approximate methods of solution. Along with the labor required for solving the equations, a tremendous work is required for identification of some of the parameters required, (see for example Ghumman A.R. 1996).

An effort is made in this study to use a neural networking technique and prepare a flood-warning scheme for rivers in Pakistan. A reach of River Chenab between Marala and Khanki is selected for this as it receives flood nearly every year for the last so many years.

2 Neural Networking Models

Artificial Neural networks are increasingly used in predicting and forecasting water resource variables (Nash, J.E. and Sutcliffe (1970), French et, M.N. (1992), Zhu, M.L. and Fujita, M. (1994), Dawson C. W. & Wilby R. L.(2001), Yi-Ming Kuo (2003)). Hydrologic models can be divided into three broad categories, namely: Physical distributed models, lumped conceptual models and black box models.

Physical based distributed models require excessive field data whereas in case of lumped conceptual models, large number of parameters and subsequent difficulty in calibration is involved. Both of these models are used where detailed understanding of the hydraulic phenomenon is necessary. Black box models do not contribute much in enhancing the understanding of hydrological and hydraulic phenomena; nevertheless in operational hydrology and hydraulic Engineering their usefulness is of utmost importance. Neural Networking models can be considered as black box models. These are easy to use and have comparatively less data requirements. This is the reason why they are becoming popular and are recently being used in the field of Water

Resources Engineering also. There are several neural network softwares. EasyNN was used in this study.

3 Training

The training process estimates the Artificial Neural Networks (ANN) weights and is similar to the calibration of a mathematical model. The ANNs are trained with a training set of input and known out put data. The weights are initialized either with a set of random values, or based upon some previous experience. These weights keep on changing till the goal is achieved. The goal of learning is to determine a set of weights that will minimize the error function.

4 Training and Validation Example

The input data of the model were taken as the observed 6 hourly discharges at Marala, River Chenab, Pakistan. The 6 hourly measured discharge data at Khanki were used as the target discharges in the EasyNN model calibration and verification. The target was to forecast flood hydrograph at Khanki. By considering the data of 1973 flood hydrograph at Marala the training was carried out. The flood data of August 1976 and 1986 was used in the model testing.

5 Data Processing

The model was run both without and with data processing. For processing purpose the data was normalized by the following formulae

$$Q_{pi} = \frac{Q_i}{Q_{\max}}$$

where Q_{pi} is processed discharge at ith time step. Q_i is discharge at ith time step and

Q_{max} is the peak discharge

After normalizing all the input values, the data was again entered into the EasyNN software. The results were used to calculate the efficiency of the model.

6 Network Architecture

6.1 Architecture – I

In the grid, two input columns in one test and four in the second case and one output column were made. The total number of training example rows were 47. The grid did not contain any validating rows and had only one querying row. The learning rate and momentum were set to be 1.0 and 0.6 respectively and were optimized. Growing layer no. 1 generated the new network with the growth rate changing after every 10 cycles or 5 seconds.

In the network two input nodes in one test and four in the second case were one output node were selected. Hidden layer no. 1 was provided with five nodes in first case and seven in second case whereas hidden layers 2 and 3 were not provided with any nodes. The first test then started learning and gave the following results.

Hidden layer	1 No.	Hidden Nodes	5 Nos
Learning Cycles	517	Learning Rate	1
Learning Momentum	0.6	Minimum error	0.002128
Average error	0.049995	Maximum error	0.228
Target error	0.05		

The second test gave the following results after learning.

Hidden layer	1 No.	Hidden Nodes	7 Nos
Learning Cycles	273	Learning Rate	1
Learning Momentum	0.8	Minimum error	0.000301
Average error	0.049738	Maximum error	0.323219
Target error	0.05		

6.2 Architecture – II

The grid was same as that in architecture-1. The learning rate and momentum were set to be 1.0 and 0.7 respectively and were optimized. Growing layer no. 2 generated the new network with the growth rate changing after every 20 cycles or 2 seconds.

In the network two input nodes and one output node were selected. Hidden layer no 1 was provided with three nodes whereas hidden layers 2 and 3 were not provided with any nodes. The network then started learning and gave the following results.

Hidden layer	1 No.	Hidden Nodes	3 Nos
Learning Cycles	677 Nos	Learning Rate	1
Learning Momentum	0.7	Minimum error	0.000951
Average error	0.049995	Maximum error	0.211899
Target error	0.05		

It was found that the first test in the former network yields a better accuracy than the other one.

7 Model Performence

The model performance was evaluated both qualitatively by the visual comparison of the simulated and observed hydrographs and quantitatively using a statistical parameter namely the Model Efficiency Index (EI) given by the following equations.

$$EI = \frac{ST - SE}{ST}$$

Where
$$ST = \sum_{i=1}^{N} (Q_{Si} - \overline{Q})^2$$

$$SE = \sum_{i=1}^{N} (Q_{Si} - Q_{Oi})^2$$

$\overline{Q} = \frac{1}{N}\sum_{i=1}^{N} Q_{Si}$, N is the number of data points. Q_{si} is simulated discharge and Q_{oi} is the observed discharge at ith time step.

8 Results and Discussion

8.1 Training and Validation Run 1

Architecture 1 was used. Data of 1973 flood was used for learning purpose and that of 1976 & 1986 was used for validation.

The observed and simulated hydrographs are shown in fig. 1 & fig. 2. It is observed from fig. 1 that observed and simulated hydrographs are similar. For two input columns, a slight variation in time to peak is observed. The E.I in this case is nearly 60%. In case of fig. 2 the simulated and observed hydrographs match with each other. The error between observed and simulated discharges is small. The value of E.I is 77.3%. In case of four input columns the EI of 1976 flood was found to be 62.32% and that for 1986 flood was found to be 79.28%.

8.2 Training and Validation Run 2

Architecture 2 was used in this test run. Data of flood hydrographs was taken as same as that in test run-2. EI in case of 1976 flood was nearly 50% and that in 1986 flood was estimated to be 30%. This architecture did not give good results

8.3 Training and Validation Run 3

Test run 1 was repeated by normalized data. It was observed that the EI was improved and came out to be 68% for the first figure and 84% for the second. The smaller EI in case of 1976 hydrograph is due to the difference in shape of hydrographs used for training and validation.

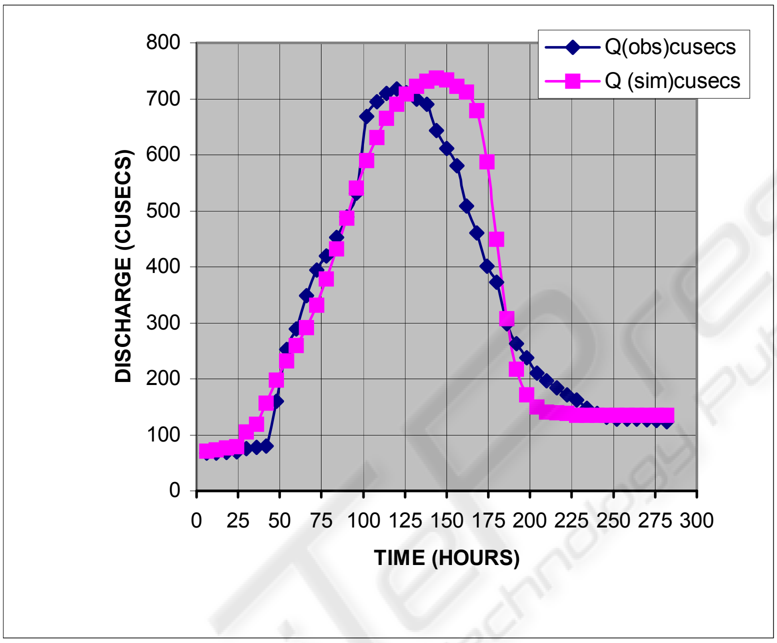

Fig. 1. 1976-Flood Hydrographs at Khanki

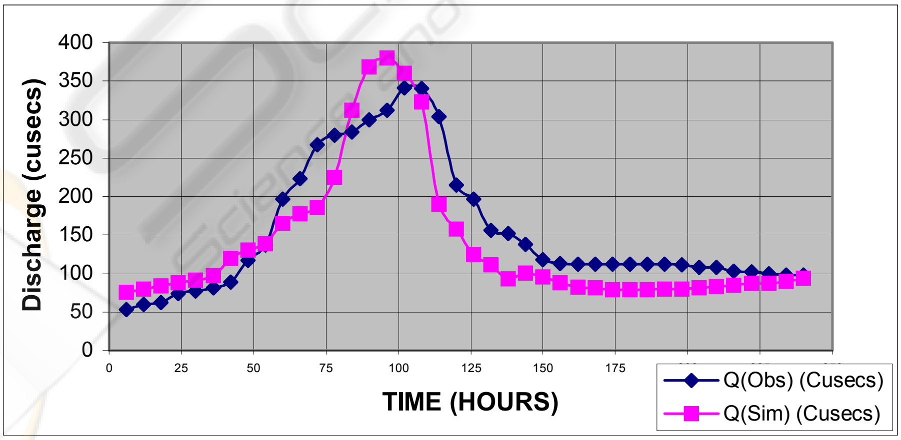

Fig. 2. 1986-Flood Hydrographs at Khanki

9 Conclusions

A neural network model for discharge forecasting at Khanki, River Chenab, Pakistan was developed. The model developed was found to perform very well in both training and validation. The efficiency index of the model was found to be about 84%. The neural network model is however still dominated by trial and error process in many aspects. It is important to mention that the selection of the network architecture significantly influences the output performance of the model and the computational time. The model requires discharge data but not the topographical data.

10 Future Recommendations

More studies are encouraged to apply neural network models for flood forecasting in other reaches of this river and other rivers of Pakistan so that the models could be applied with confidence in operational flood forecasting and warning.

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