Bulletin of Environment, Pharmacology and Life Sciences
Bull. Env. Pharmacol. Life Sci., Vol 3 (4) March 2014: 99-102

Online ISSN 2277-1808
Journal's URL:http://www.bepls.com
CODEN: BEPLAD
Global Impact Factor 0.533
Universal Impact Factor 0.9804

ORIGINAL ARTICLE

An Artificial Neural Network Approach for Predicting Floodplain

Ali Abbasinejad[1], Ali Afrous[2], Najaf Hedayat[3]

1- Department of hydraulic structures, Dezful Branch, Islamic Azad University, Dezful, Iran
2- Department of water engineering, Dezful Branch, Islamic Azad University, Dezful, Iran
3- Department of hydraulic structures, Dezful Branch, Islamic Azad University, Dezful, Iran

ABSTRACT

Conceptual models are considered to be the best choice for describing the hydrological and/or hydraulic process in a river. However, enormous requirements for topographic, hydrologic and meteorological data and extensive time commitment for calibration of conceptual models are often prohibitive factors in their practical applications. Artificial neural networks (ANN) can be an efficient way of modeling the runoff process in situations where explicit knowledge of the internal processes is not available. An ANN is a flexible mathematical structure that is capable of identifying complex nonlinear relationships between input and output data sets. This paper presents the use of ANN for predicting the floodplain values. The ANN generated results are evaluated using error functions. For five scenarios the correlation coefficients are 76%, 62%, 67%, 57% and 45%, respectively.

Keywords: ANN, Karkheh River, Floodplain.

Received 20 /01/2014 Accepted 04/03/2014

INTRODUCTION

A reasonable prediction of hydrological parameters not only provides useful information for management of water resources, but also reduces losses to life and property caused by related events. Floodplain prediction has been an active area of research in surface water hydrology and will remain so in the foreseeable future because of the uncertainties associated with both the meteorological and hydrological parameters causing flood events. Predicted factor is also vital for the economic analysis of flood management alternatives. With increasing population and economic activity in floodplains and along major rivers the importance of accurate prediction is increasing. Several techniques have been developed ranging from empirical or statistical relationships to detailed mathematical models. While empirical or statistical relationships can provide magnitude and frequency of floods, they are not capable of generating a factor with complete information [1,2].

Though frequency analysis of past flood peaks can provide information on the risk, it is limited by its lack of consideration of the forcing factors producing floods. Mathematical models, based on the consideration of physical processes, have been divided into two categories in the literature, i.e. conceptual models, or black box models. Conceptual models, based on characteristics of model parameter and variables, can be further divided into two categories, i.e. distributed and lumped models. Both distributed and lumped models are designed to approximate the general processes and physical mechanisms, which govern the hydrologic cycle. In terms of data requirement, simple black box models and highly sophisticated distributed conceptual models fall on two extreme ends of a spectrum, while lumped conceptual models with moderate data requirement are somewhere in the middle. Due to the realistic representation of watershed topography and ability to capture surface and ground water interaction, the most desirable method to predict runoff hydrograph is a distributed conceptual dynamic hydrologic model [2-4].

However, extensive topographic, meteorological, and hydrologic data required to describe such process and time needed to calibrate conceptual models (especially distributed models) are important factors to be considered in their practical applications [5].

Implementation and calibration of conceptual models (especially distributed models) can typically present various difficulties, requiring sophisticated mathematical modeling tools, significant amount of calibration data, and some degree of expertise and experience with the model [6].

While conceptual models are of importance in the understanding of hydrologic processes, there are many practical situations, such as runoff prediction, where the main concern is with making accurate predictions at specific locations along a river. In such a situation, a hydrologist may prefer not to expend the time and effort to develop and implement a conceptual model and instead may choose to implement a simpler black box model. In the black box approach, difference/differential equation models are used to identify a direct mapping between the inputs and outputs without detailed consideration of the internal structure of the physical processes. The linear time series models, such as ARMAX (auto-regressive moving average with exogenous inputs) model have been most commonly used in such situations because they are relatively easy to develop and implement. ARMAX type model has been found to provide satisfactory predictions in many applications where input–output characteristics are approximately linear, e.g. forecasting water level or discharge at a point along the river based on a water level or discharge value at some location upstream of that point. However, such models do not attempt to represent the nonlinear dynamics inherent in the transformation of snow/rainfall to runoff and therefore may not always perform well. Based on the success of ANN in the field of water resources, and working with an assumption that simplest model that can satisfactorily describe the system for the given input data should be used, artificial neural networks (ANN), belonging to the class of black box models, are explored in this paper for the development of runoff hydrograph. This paper outlines a general framework for developing a runoff hydrograph using artificial neural network approach [7-12]. While such a model is not intended as a substitute for a conceptual model, it can provide a viable alternative when the hydrologic application requires that an accurate forecast of stream flow behavior be provided using only the available time series data, and with relatively moderate conceptual understanding of the hydrologic dynamics of the particular watershed under investigation [12-17].

MATERIAL AND METHOD

The general structure of artificial neural network is inspired from human neural system and is capable of performing an approximately same mission but in preliminary stages. These systems process the available data, to transfer and also maintain the hidden laws. Therefore they are usually known as intelligent systems. Perceptron neural network is a multiple forward network which includes an input layer, one or some hidden layers and an output layer. Input nodes percepts the information from outside and the results are measured from neurons of output layer. The forward network provides a response in a forward direction from input information. In other words it has no feedback. Besides, the joints of this network is complete i.e. each neuron in each layer is connected to all of the next layer neurons. Error functions which are used for evaluating the performance of the models are expressed by the followings (Eq. 1-3):

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|O_i - P_i\right| \tag{1}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(O_i - P_i)^2}{N}} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \overline{O}_i)^2} \tag{3}$$

Where *O* is the observed parameter, $\overline{O}$ is the average of observed parameters, *P* is the model predicted parameter and N is the number of data. Different scenarios are also prepared which is summarized in table 1. Not to mention that y and w stands for the depth and width of the research respectively.

Table 1. Different scenarios used in the research

Scenario No.	input	output
1	Y and w	floodplain
2	(y/w)*1000	floodplain
3	y	floodplain
4	w	floodplain
5	1.15y and 1.15w	floodplain

RESULTS AND DISCUSSION

A feed forward artificial neural network with back-propagation algorithm is used to estimate the floodplain of the river.

Based on the available historic data on flood events, five causal parameters, which play an important role in flood generation, have been identified.
These five meteorological parameters that also have physical base are used as input to the neural network model.
The network has been trained to predict eight output parameters that are used to describe a complete runoff hydrograph. ANN model has been trained using historic data and verified on a different data set never seen by the network. The proposed approach is implemented for the Karkheh River. The neuro-computing approach for developing runoff hydrograph is presented along with details on input and output parameters of neural network model. The paper finally concludes with a discussion of results. The results are obvious in figure 1 and 2 while the statistical evaluation is presented in table 2.

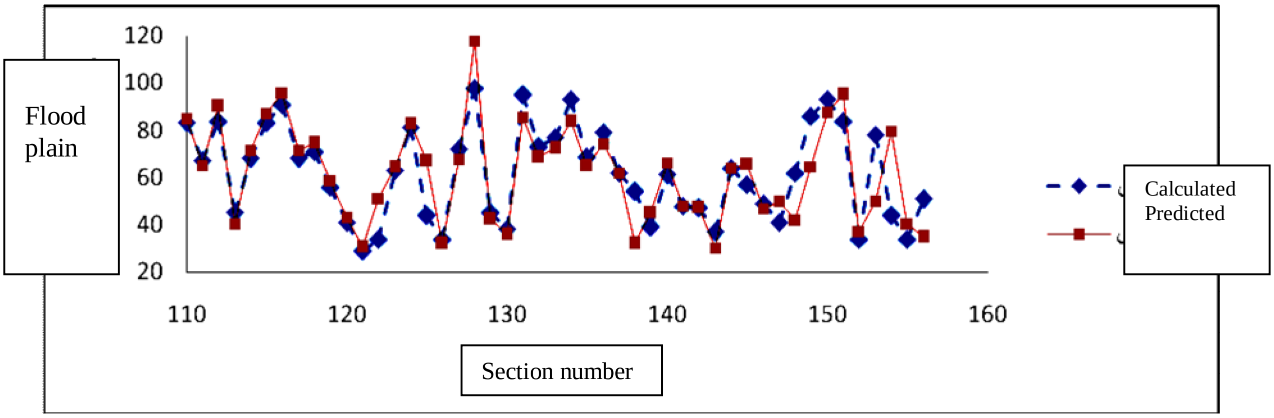

Figure 1- the comparison of flood plain values in the first scenario

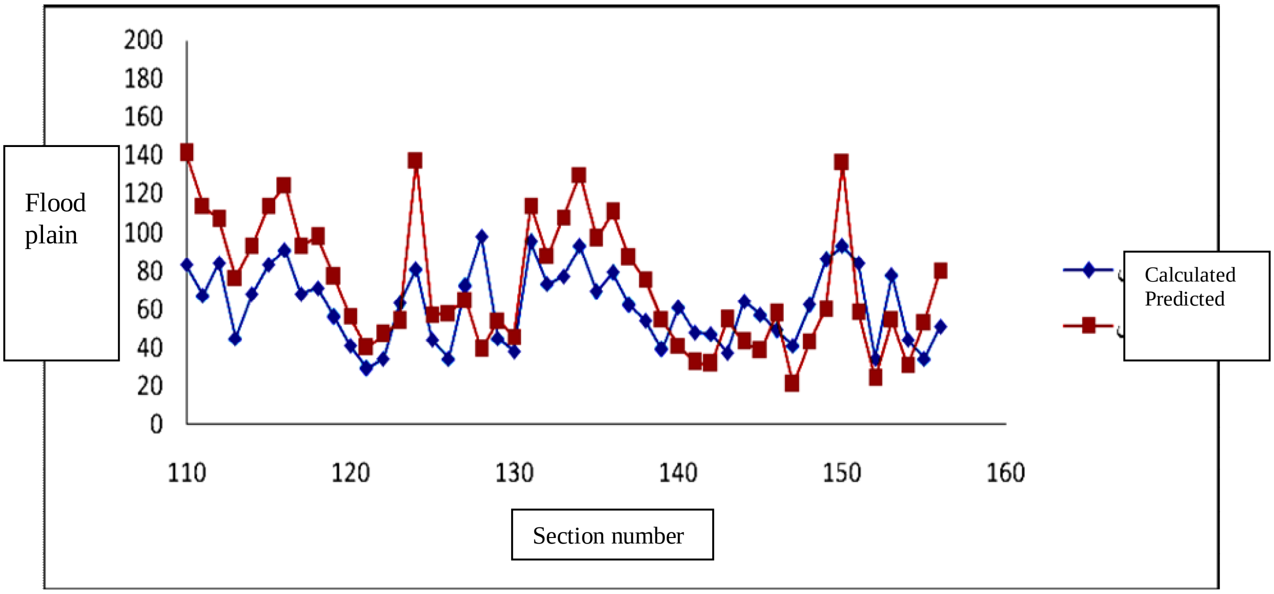

Figure 2- the comparison of flood plain values in the fifth scenario

Table 2- the evaluation of different ANN scenarios

Scenario No.	MAE	RMSE	RE
1	0.33	0.46	0.13
2	0.47	1.25	0.25
3	0.38	1.15	0.21
4	0.53	1.47	0.35

CONCLUSION

This paper presented the use of ANN for predicting the floodplain values. The results were evaluated. For five scenarios the correlation coefficients were 76%, 62%, 67%, 57% and 45%, respectively. This approach for estimating a flood hydrograph is almost appropriate and can be applied to other locations in the Karkheh River basin or to other rivers having similar flood characteristics.

Transferring the model to any other location in the River will require training the network for output parameters at that location, while using same input parameters. For watersheds that are similar in characteristics (e.g. runoff, topography), same architecture of ANN, in terms of input and output parameters, can be used, but data is watershed specific. There are simulation scenarios, in addition to what has been demonstrated in this study that can be tested using the existing framework. Training the model in reverse, i.e. using output parameters as input, a scenario of hydrologic and meteorological conditions can be identified that may lead to a catastrophic flood.

REFERENCES

1. Peter A. Nelson, Dino Bellugi, William E. Dietrich, (2012). Delineation of river bed-surface patches by clustering high-resolution spatial grain size data, Geomorphology, In Press, Corrected Proof — Note to users
2. Yaolin Liu, Limin Jiao, Yanfang Liu, Jianhua He. (2012). A self-adapting fuzzy inference system for the evaluation of agricultural land. Journal of environmental software.09.013.
3. Michael C. Slattery, Jonathan D. Phillips, (2011). Controls on sediment delivery in coastal plain rivers. Journal of Environmental Management, Volume 92, Issue 2, , Pages 284–289
4. Katie H. Costigan, Melinda D. Daniels, (2012). Damming the prairie: Human alteration of Great Plains river regimes, Journal of Hydrology, Volumes 444–445,90–99.
5. Q.H. Zhao, S.L. Liu, L. Deng, S.K. Dong, C. Wang, J.J. Yang, (2012). Assessing the damming effects on runoff using a multiple linear regression model: A case study of the Manwan Dam on the Lancang River ,Procedia Environmental Sciences, Volume 13,1771–1780
6. W. Ouyang, F.H. Hao, K.Y. Song, X. Zhang. (2011). Cascade Dam-Induced Hydrological Disturbance and Environmental Impact in the Upper Stream of the Yellow River, Water Resour Manage, 25 (3) pp. 913–927
7. F. Lajoie, A.A. Assani, A.G. Roy, M. Mesfioui, (2007). Impacts of dams on monthly flow characteristics, The influence of watershed size and seasons. J Hydrol, 334 (3–4), pp. 423–439
8. J.K. Maingi, S.E. Marsh. (2002). Quantifying hydrologic impacts following dam construction along the Tana River, Kenya. J Arid Environ, 50 (1), pp. 53–79
9. P. Zeilhofer, R.M. de Moura. (2009). Hydrological changes in the northern Pantanal caused by the Manso dam: Impact analysis and suggestions for mitigation, Ecol Eng, 35 (1) , pp. 105–117
10. K. Tockner, J.A. Stanford, (2002). Riverine flood plains: present state and future trends, Environ Conserv, 29 (03) (2002), pp. 308–330
11. D.L. Galat, R. Lipkin, Restoring ecological integrity of great rivers: historical hydrographs aid in defining reference conditions for the Missouri River, Hydrobiologia, 422 (2000), pp. 29–48
12. Naik PK, Jay DA. Distinguishing human and climate influences on the Columbia River: changes in mean flow and sediment transport. J Hydrol 2011.
13. Q.H. Zhao, S.L. Liu, S.K. Dong, Effect of Dam Construction on Spatial-Temporal Change of Land Use: A Case Study of Manwan, Lancang River, Yunnan, China. Procedia Environ Sci, 2 (2010), pp. 852–858
14. Ibraim Fantin-Cruz, Olavo Pedrollo, Nilza M.R. Castro, Pierre Girard, Peter Zeilhofer, Stephen K. Hamilton., Historical reconstruction of floodplain inundation in the Pantanal (Brazil) using neural networks. Volume 399, Issues 3–4, 18 March 2011, Pages 376–384
15. Yuhui Wang, Hao Wang, Xiaohui Lei, Yunzhong Jiang, Xinshan Song. Flood simulation using parallel genetic algorithm integrated wavelet neural networks, Volume 74, Issue 17, October 2011, Pages 2734–2744
16. Mahesh R. Gautam, Kunio Watanabe, Hiroyuki Ohno. Effect of bridge construction on floodplain hydrology—assessment by using monitored data and artificial neural network models, Volume 292, Issues 1–4, 15 June 2004, Pages 182–197
17. Mrutyunjaya Sahu, K.K. Khatua, S.S. Mahapatra. A neural network approach for prediction of discharge in straight compound open channel flow. Volume 22, Issue 5, October 2011, Pages 438–446

How to cite this article:
Ali A, Ali A., Najaf H. An Artificial Neural Network Approach for Predicting Floodplain.Bull. Env.Pharmacol. Life Sci. 3 (4) 2014: 99-102