Neural Networks and Rainfall-Runoff Model, its Calibration and Validation

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Abstract. In this study a rainfall-runoff model was developed with the help of neural networks. Input to the model is precipitation and potential evapotranspiration (both on monthly basis). Output from the model is the simulated runoff at the watershed outlet. The model was calibrated and tested for Brandu river catchment of Pakistan.The data was collected from Meteorological Department Pakistan. Statistical results showed that the model preformed well. The correlation co-efficient between the simulated and measured data was found to be 87.5%.

1 Introduction

Structural and non-structural designs of some hydraulic structures, reservoir operation and water resources development projects need river flow hydrographs. For such hydrographs simulation of watershed response to hydrologic inputs is required.

Various researchers have developed monthly water balance models, Pitman (1973), Mather (1981), Alley (1984), Vandewiele et al (1992), Xu & Vandewiele (1995), Huges (1995) and Vandewiele et al (1998). These models are rarely static. They undergo frequent modifications by their developer or by a subsequent user. Stefan et al (1999), Liden (2000), Madsen (2000) and Shan (2000) studied the performance of a conceptual rainfall runoff models. The complexity of models varies according to data availability, type of hydrologic quantity to be modeled, scale of operation, required accuracy, computer facilities and economic considerations. Generally, there is no universal model, which could be applied successfully to all hydrologic basins as the natural processes are highly random and models are data dependent.

Neural network techniques have provided solution to this problem up to some extent. Although these models do not provide understanding of the watershed response but still the model results have many important applications. Researchers in the field of Hydrology have started modeling using neural networks Oscar R.Dolling & Eduardo A.Varas (2002); Tawatchai Tingsanchali (2003) ; Yi-Ming, Kuo Chen – Wuing Liu & Kao-Hung Lin(2004).

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The present study is an effort to address the problem of simulating runoff from a watershed with the help of neural networks. A mathematical model was developed and run on a P-IV computer. The model was tested using measured data of watershed. Statistical tests were performed to examine the performance of the model.

2 Description of the study areas

The watersheds selected for calibration and validation of the model was based on two criteria: (a) there is no snow melt contribution to total runoff which cannot be simulated by the model, (b) a continuous record of observed runoff is available, which is used for calibration and validation of the model. Brandu River Watershed, was selected for study.

Brandu River Watershed is located in Swat district of NWFP, Pakistan. The elevation ranges between 732 m to 2134 m above mean sea level. The drainage area of Brandu River is 598 km^2. The climate of the study area is sub-tropical sub-humid continental, and has a record of 1025.72 mm mean annual precipitation. The soils and landforms are loess plains, piedmont plains, river alluvium and miscellaneous areas (rough broken land, gulled land, rough mountainous land, stony land). The land in the valley of the study area is cultivated and has good vegetation cover due to the availability of very shallow groundwater, whereas the hill slopes of the watershed are sparsely vegetated. The main season of rainfall in the study area is the monsoon from July to September, which is the major contribution of flow in the river. The other seasons of the year have low rainfall rate, but occasionally high storms of single event do occur. Therefore high flows in the river are occurring during summer season and low flows during the other seasons. Baseflow and groundwater are contributing to the Brandu River flows. This is indicated from some high flows against low rainfall rate from the data of the watershed and reported studies of the area (Soil Survey of Pakistan 1975). According to this the groundwater is available at shallow depths.

3 Neural networking Models

As mentioned in our first paper the 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. EasyNN model based on Neural Networking was used to simulate runoff from a catchment area.

4 Training

This has also been described in our first paper submitted for this conference. 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.

5 Training and Validation

The input data of the model were taken as the observed monthly rainfall and evaporation for Brandu River Catchment. The monthly measured runoff data for the same catchment were used as the target in the EasyNN model calibration and validation. The aim was to forecast monthly runoff from the catchment if rainfall and evaporation is known. By considering the data from1971-1980 the training was carried out. This was done in twelve steps taking ten years data for a specific month for each step. For validation the measured data of rainfall, evaporation and runoff for 1981 to 1989 was used.

6 Calibration and Validation tests

Ten years (1971 to 1980) rainfall runoff and evaporation data was used for model calibration. The model was tested using other set of data from 1981 to 1989 for the same catchment. Statistical analysis was performed using four statistical parameters, mathematically given as (Mutreja 1986):

$$C_c = \sqrt{\frac{\sum\left[(R_c)_j - \overline{R}_o\right]^2}{\sum\left[(R_o)_j - \overline{R}_o\right]^2}} \tag{1}$$

$$C_d = (C_c)^2 \tag{2}$$

$$S_e = \sqrt{\frac{\sum_{j=1}^{N}\left[(R_o)_j - (R_c)_j\right]^2}{N}} \quad (3)$$

Where: C_c is coefficient of correlation, C_d is coefficient of determination and S_e is standard error of estimates. $\overline{R}_o$ is mean observed runoff and is equal to

$\overline{R}_o = \frac{1}{N}\sum(R_o)_j$, where N is the length of record.

7 Results and Discussion

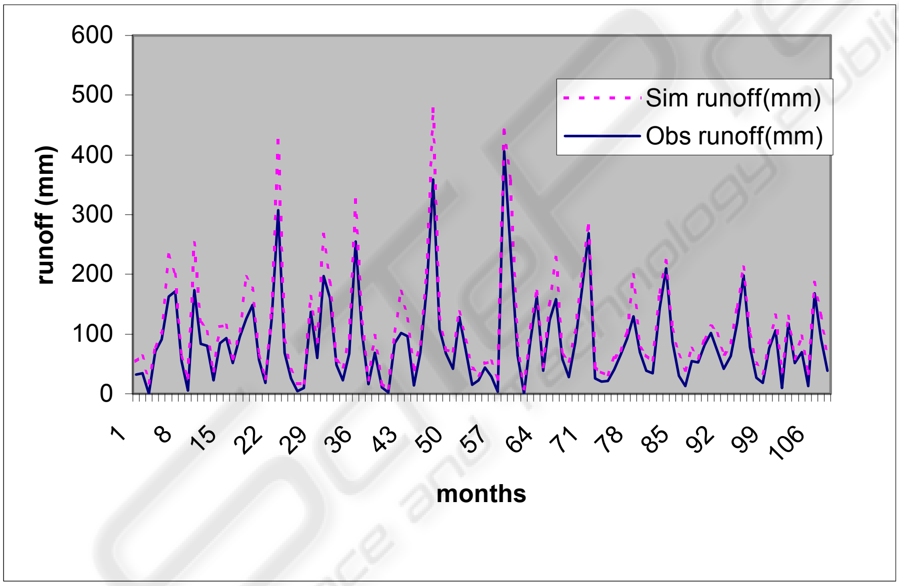
Figures 1 presents a comparison between observed and simulated run off .The graphs shows good similarity between observed and simulated runoff. The goodness of fit of these graphs is measured by three statistical parameters, C_c, C_d & S_e which were described in previous section. . The results of these tests are given in table 1.

The model developed in this study performed well. The statistical measures in case of calibration have better results than that in case of verification. It usually happens that the error variance during validation is in excess of the error variance during fitting period.

Table 1 shows that model developed in this study performed better than the Pitman model although the present model is a black box model.

Table 1. Results of statistical tests (Validation of model).

Watershed	Statistical Parameter	Developed Model	Pitman Model (from M.S.Abulohom.2001)
	C_c	0.875	0.81
Brandu River	C_d	0.766	0.67
	S_e	8.9	11.96



8 Conclusions

A model has been developed which is robust and works as black box model. The model has a good performance over a wide range of climatic conditions. Working with measured data of rainfall and runoff requires great efforts for calibrating model parameters due to the influence of the quality of observed data. Because the parameters act as "catch all parameters", black box model based on neural networks can be adopted for such conditions, thus reducing complexity of calibration and the problem of non-availability of data required for the analysis.

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