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Using Artificial Neural Network for Real Time Flood Prediction in River Jhelum, J&K (India)

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ABSTRACT
The application *of* artificial neural network (ANN) methodology for modeling flood prediction for a large size catchment of the river Jhelum in Jammu and Kashmir (India) is presented. Development of flood prediction models for river Jhelum, flowing through the Srinagar city (J and K) based on the tail side discharge of upstream tributaries is studied because major inundation caused due to the floods in river Jhelum occurs in the highly populated and largely developing city of Srinagar. The 22 years data records between the years 1990-2012 were used and ANN technique along with conventional regression analysis was employed. The performance was compared based on statically parameters root mean squared error (RMSE), mean square error (MSE), coefficient of determination (R^2) and absolute average deviation (AAD) values. NN_{tp} model emerged as the best model with the highest value of R^2 compared to other models as 0.93, value of MSE and RMSE being the least as 0.008 and 0.09 respectively. The study proved ANNs to be much better in predicting the flood discharge when judged on all the above parameters. It also showed that transfer function tan-sig performs better than pure-lin in the networks developed for flood prediction. The flood discharge could be thus predicted at least a day before the discharge reaches the station with a high predictability based on the ANN model NNtp.

Introduction

Data-driven methods offer an alternative approach to more traditional conceptual and physically-based hydrological models as they are not built using knowledge of the underlying physical processes. Instead these techniques use the data to induce relationships. For example, multiple linear regression technique allows additional factors to enter the analysis separately so that the effect of each can be estimated. It is valuable for quantifying the impact of various simultaneous influences upon a single dependent variable. Regression analysis determines the values of parameters for a function that cause the function to best fit a set of data observations that we provide. Likewise artificial neural networks ANNs, use an input-output training set to learn the relationships from the data. Once the relationship is learned, the model is deterministic and can be used to make prediction from input data. Artificial neural networks (ANN) offer a relatively quick and flexible means of modeling and thus application of ANN based modeling are widely reported in literature. The American Society of Civil Engineers (ASCE) Task Committee[1]-[2] summarized application of ANN for the solution of many hydrological problems. Artificial neural networks have been used for stream flow forecasting and have been reported in literature. [4-5], [7] , [11] [8-9], [14-15], to perform much better than the conventional models. The supremacy of the multilayer feed forward neural network (MLFN) over the regression model in terms of predictive power for the same data have been demonstrated [12]. Compared predictive results of NNs and a neuro-fuzzy approach to the predictions of two linear statistical models, auto-regressive moving average and auto-regressive exogenous input models have been reported [3] ,with the neuro network and the neuro-fuzzy system both superior to the linear statistical models. Use of neuro networks for flood estimation at sites in ungaged catchments have been attempted [6]. auto-regressive moving average and auto-regressive exogenous input models have been reported [3] ,with the neuro network and the neuro-fuzzy system both superior to the linear statistical models. Use of neuro networks for flood estimation at sites in ungaged catchments have been attempted [6].

In the present study, an attempt has also been made to model the physical process of rainfall -runoff within the frame work of ANN. The flood problem in the Kashmir arises primarily from the inadequate carrying capacity of the river Jhelum in its length flowing through Srinagar city, situated along both the embankments of the river which adds to the difficulty of keeping the city safe from the inundation. A quick and accurate flood forecasting is required particularly in flood prune areas in order to allow ample time for evacuation of population endangered. ANN models and MLR model were compared based on their statistical performance evaluators, root mean squared error (RMSE), mean square error (MSE), coefficient of determination (R^2) and absolute average deviation (AAD) values. The study proved ANNs to be much better in predicting the flood discharge when judged on all the above statistical parameters. It also showed that transfer function tan-sig performs better than pure-lin in the networks developed for flood prediction. The flood discharge could be thus predicted at least a day before the discharge reaches the station with a high predictability based on ANN model NNtp

Material and Methodology

Study AREA

River Jhelum flows through India and Pakistan having a total length of about 725 kilometers. River Jhelum rises from Verinag spring situated at the foot of the Pir Panjal in the south-eastern part of Kashmir valley in India. It flows through Srinagar city, the capital of Jammu and Kashmir and the Wular

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lake before entering Pakistan. It ends in a confluence with the river Chenab. Srinagar city which is the largest urban centre in the valley is settled on both the sides of river Jhelum and is experiencing a fast spatial growth. The river Jhelum and its associated streams that drain the bordering mountain slopes together constitute the drainage network of the study area. They include the fairly developed systems like Sind, Rambiara, Vishaw and Lidder rivers as well as tiny rivulets such as the Sandran, Bringi and Arapat Kol. The study area chosen spatially lies between 33° 21' 54" N to 34 ° 27 ' 52" N latitude and 74° 24' 8" E to 75° 35' 36" E longitude with a total area of 8600.78 km^2. Fig. 1 shows the location map of study area. The drainage network and the flood plain map of the study area is represented in Fig. 2.

Data Selection/ Data Normalization

The daily rainfall data for the years 1990-2012, the tail side daily discharges of the upstream tributaries of river Jhelum and at the Padshahi Bagh gauging station on river Jhelum for the years 1990-2012 and the daily gauges of the selected tributaries and at Padshahi Bagh station was made available from the Irrigation and Flood Control Department, Srinagar Kashmir. The selection of the data for the flood discharge prediction was made based on the major rainfall events. The lag between the flows of the river from the various tributaries to the main river at Padshahi Bagh station was suitably considered with a maximum lag of 2 days for the upper reach tributaries and of 1 day for the middle reach tributaries and of few hours for the lower reach tributaries[13]. Due to the non-availability of the daily measured discharge for all the tributaries, the discharges of all the tributaries and the Padshahi Bagh station on the dates selected as per the rainfall events were inferred from the stage-discharge

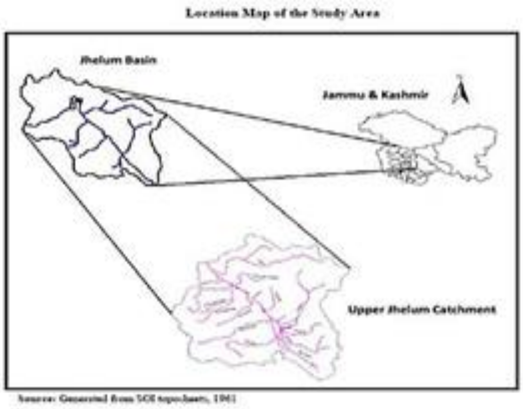

Figure.1 . Location Map of Study Area

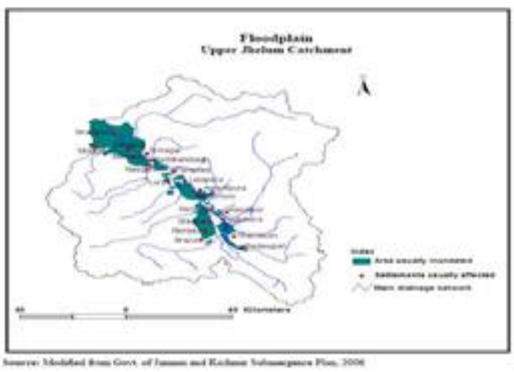

Figure.2. Drainage map of study area

curves as the daily gauges were available. After the data selection, the data was normalized between -1 to 1 using the MATLAB 7.0.1 software. The normalized data consisted of 280 sets. The data was divided into training and validation sets. The training set consisted of 80% of the data and the validation set consisted of the 20% of the data.

Artificial Neural Networks

An ANN is an information -processing paradigm inspired by biological nervous system such as our brain, [10]. Generally for different types of ANNs, there is an input layer receiving inputs from the environment, one or more intermediate layers and an output layer producing the network response. In this study, feed forward back propagation (FFBP) was selected for predicting because it is the most commonly used ANN approach in hydrological predictions [14] . The training data was first analyzed using Microsoft Excel and Mini tab 13.31 software. Multiple linear regression was conducted and the model for flood prediction generated. The training data set was then saved into MATLAB 7.0.1 software in the form of input matrices of 6×11 and target matrices of 6×1. Initially single layer perception based feed forward ANN which uses back-propagation learning algorithm was applied for modeling followed by double layered perception based feed forward ANN using back propagation learning algorithm. Two types of transfer functions namely; pure-lin and tan-sig were used to develop four types of networks. The first two networks consisted of an input layer with eleven input parameters, one hidden layer consisting of 11 neurons and an output layer and pure-lin and tan-sig as transfer functions respectively. The latter two networks consisted of an input layer with eleven input parameters, two hidden layers with 11 neurons in first hidden layer and a single neuron in second layer and the combination of pure-lin and tan-sig as transfer functions; with pure-lin in first layer and tan-sig in second respectively; and the second with tan-sig in first and pure-lin in second respectively.

Model Performance Evaluation

The performance of the predictions resulting from training and testing was evaluated by measures of goodness of fit i.e. mean squared error MSE or root mean squared error RMSE, coefficient of determination R^2 and Absolute average deviation AAD expressed in the following equations;

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_p - y_a)^2 \qquad (1)$$

$$\mathrm{RMSE} = (\mathrm{MSE})^{\frac{1}{2}} \qquad (2)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_p - y_a)^2}{\sum_{i=1}^{n}(y_a - y_m)^2}, \qquad (3)$$

$$\mathrm{AAD} = \{[\textstyle\sum_{i=1}^{n}(|y_p - y_a|/y_a)]/n\} \times 100 \qquad (4)$$

where y_a represents the actual observed value; y_p is predicted value and n represents the number of observations considered. Additionally a multiple linear regression model as an alternate method was applied for evaluating the models performance statistically.

Result and Discussion

In order to improve the predictability of the neural networks, four different networks were trained and developed. Starting with simplest one with single layer and pure-lin function, the complexity was increased until the best results were got with a combination of two hidden layers with tan-sig in first layer comprising of 11 neurons and pure-lin in the second. The performance of the trained networks with different hidden layers and transfer function was measured by performing a regression analysis between the network response and the corresponding targets. The un-normalized network output 'a' is in the same units as the original targets 't'. Fig. 3 to Fig. 6 represents the scatter plots of the network outputs versus the targets as open circles. The best linear fit is indicated by a solid line.

Table 1. Comparative performance of various model

Network	Hidden layers	Transfer function	Neurons	MSE	RMSE	R^2	AAD
MLR	-	-	-	0.0204946	0.1431594	0.835	0.2776616
NN_p	Single	pure-lin	11	0.020656	0.14372	0.829124	0.3397264
NN_t	Single	tan-sig	11	0.009394	0.096922	0.922289	0.207275
NN_{pt}	Double	Pure-lin in first tan-sig in second	11, in first layer 1, in second layer	0.020656	0.14372	0.829124	0.3397264
NN_{tp}	Double	tan-sig in first Pure-lin in second	11, in first layer 1, in second layer	0.008899	0.094336	0.926381	0.3001107

The perfect fit (output equal to targets) is indicated by the dashed line. The results of the different networks along with traditional regression analysis for the validation are compared graphically with the corresponding observed values of discharges in Fig.7. Table I shows the details of indicators namely MSE, RMSE, R^2 and AAD for the different seniors considered.

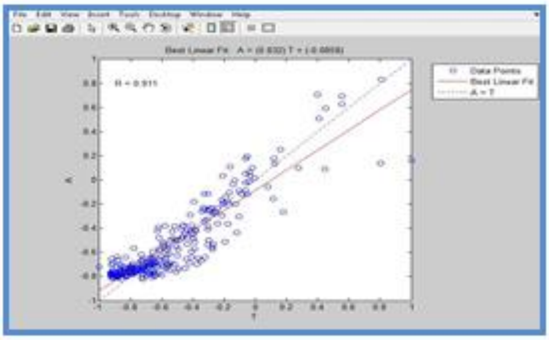

Figure 3. Scatter Plot for Network NNp

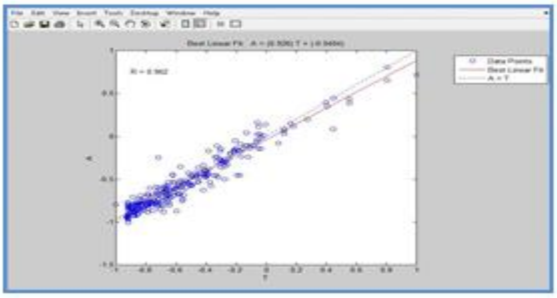

Figure 4. Scatter Plot for Network NNt

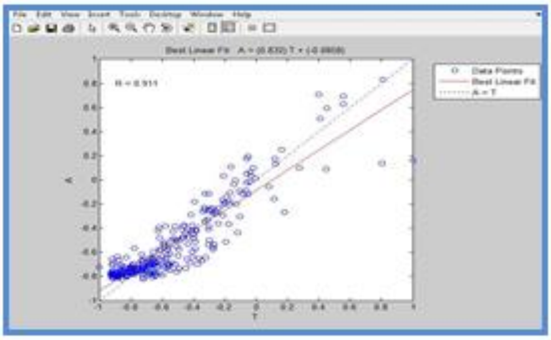

Figure 5. Scatter Plot for Network NNpt

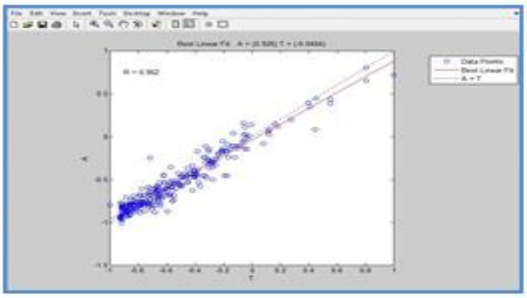

Figure 6. Scatter Plot for Network NNtp

Tabular results and plots revealed that the MLR and neural network generated show high correlation between the actual and the predicted discharges of river Jhelum at Padshahi Bagh station. The figure shows that the predicted discharges and the actual discharges show lesser variations for the neural network models as compared to the MLR model. The NN_{tp} model with increased number of hidden layers with more neurons in the layer with pure-lin transfer modeling result better performance with a high coefficient of determination (R^2=0.93) in predicting the flood discharges in river Jhelum at Padshahi Bagh station.

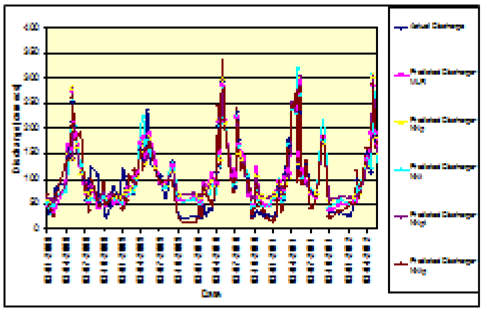

Figure 7. Comparison Actual and Predicted Discharges

The figure shows that the predicted discharges and the actual discharges show lesser variations for the neural network models as compared to the MLR model. The NN_{tp} model with increased number of hidden layers with more neurons in the layer with pure-lin transfer modeling result better performance with a high coefficient of determination (R^2=0.93) in predicting the flood discharges in river Jhelum at Padshahi Bagh station based on the discharge of the upstream tributaries. The results obtained by the five models are however close to each other as well as to original values.

Artificial neural network emerged as a better technique in predicting the flood discharge in the cases where prior knowledge of the catchment characteristics is not known. The ability of neural network to get trained and then once trained to show level of predictability, proves it most most promising technology for flood prediction.

Conclusions

In this study, the applicability of artificial neural networks technique was investigated in flood discharge prediction in river Jhelum without prior knowledge of the features of the watershed by conventional regression analysis and all selected neural network configurations. NN_{tp} network (R^2=0.93). gave better results than MLR, NN_p, NN_t and NN_{pt} networks, revealing that the model was superior over other four. NN_t model (R^2=0.92) gave much better results compared to NN_{pt} ; making apparent the fact that by increasing the number of hidden layers with more neurons in the layer with pure-lin transfer function showed inferior results in predicting the discharge compared to the neural network with single layer and more number of neurons with tan-sig transfer function. Feed forward back propagation perform better than the conventional regression analysis methods. Based on results, use of FFBP for flood prediction in river Jhelum is justified.

Acknowledgement

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