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Estimation of Yield Sediment Using Artificial Neural Network at Basin Scale

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Abstract: Forecasting of sediment discharge in river on regional scale is very important process for water resources assignment development and managements. The sediment yield is usually calculated from the direct measurement of sediment concentration of river or from sediment transport equations with hydrological stations in basin outlet point. Apparatus direct measurement is very costly and cannot be perform for all river measurement stations also in some basins are station miss. However, total sediment transport equations do not correspond with each other and require many detailed data on the flow and sediment characteristics. ANN model has the capability of identifying complex nonlinear relationships between inputs and output data sets. The rainfall-runoff relationship is one of the most complex hydrologic phenomena due to the tremendous spatial and temporal variability of the watershed characteristics and unpredictable rainfall pattern. The capability of ANN model for mapping the nonlinearity makes it a suitable tool for assessing the hydrological impacts of land modification and determine rate produce yield sediment in basin down stream. In general, the forecasting performance of ANN techniques is found to be advanced to the other predictable statistical and stochastic methods in terms of the selected performance standard. The ANN is well known as a flexible mathematical structure and has the ability to generalize patterns in imprecise or noisy and ambiguous input and output data sets. The study area is sorkhab River in upstream DEZ basin, IRAN country..This paper presents the proposed ANN model and Multiple Regression (MR) for prediction of total sediment at basin scale. Results show that estimated rate of sediment yield by Artificial neural networks is much better fits with the observed data in comparison to MR model. So that the differences between the estimated and the measured amount of sediment yield were respectively for Artificial neural networks model.

Key words : Artificial neural network ,MLP ,Sediment yield, Keshvar station, Multiple Regression

INTRODUCTION

Artificial Neural Network (ANN) is a flexible mathematical structure, having strong similarity to the biological brain and therefore a great deal of the terminology is borrowed from neuroscience.ANNs are gaining popularity, especially over the last few years, in terms of hydrological applications. Since the early nineties, it has been successfully used in hydrology related areas such as rainfall runoff modeling, stream flow forecasting, ground water modeling, water quality, water management policy, precipitation forecasting, hydrologic time series, and reservoir operations. Most hydrologic processes exhibit a high degree of temporal and spatial variability and are further plagued by issues of non linearity of physical processes, conflicting spatial and temporal scales, and uncertainty in parameter estimates. The time and effort required in developing and implementing such complicated models may not be justified. Simpler neural network forecasts may therefore seem attractive as an alternative tool. While conceptual models are of importance in the understanding of hydrologic processes, there are many practical situations such as stream flow forecasting where the main concern is with making accurate predictions at specific watershed locations. In such a situation, a hydrologist may prefer not to expand the time and efforts required to develop and implement a conceptual model and instead implement a simpler theoretic model. Traditionally, feed forward networks, where nodes in one layer are only connected to nodes in the next layer, have been used for prediction and forecasting applications. In the past decades, great strides have been made in conceptualizing the runoff and sediment yield processes from watersheds through modeling. Models are classified based on their comprehensiveness in representing the

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physical processes involved.With increasing comprehensiveness, models are classified as black-box models, conceptual models and physically based distributed models. The last of the three can be considered the better choice in a rigorous theoretical sense. However, the significant data need of such models and their marginally superior results compared to the others make them an Unfavorable choice in operational hydrology Gautam *et al*. (2000),Gautam *et al*. (2000). Lumped conceptual models are favored, as they can be based on a sound conceptual framework due to their limited data need. But they require lengthy calibration and parameterization processes. Amongst the soft computing tools viz. Genetic Algorithm (GA), Simulated Annealing (SA), Multivariate Adaptive Regression Splines (MARS) and Artificial Neural Networks (ANNs), the ANNs are most frequently used for hydrological modeling. The first fundamental concepts related to neural computing were developed by MCCULLOCH and Pitts (1943), and much of the ANN activities have been centered on back-propagation and its extensions Salas *et al*. (2000). The ANN technique mimics the cognitive response of the human brain. The ANN functions as a data-mining tool, in which the input and output data set has to be fed to the software and trained before validating the model. The network function is determined by the connections between elements. The neural networks need to be trained to perform a particular function by adjusting the values of the connections (weights) between elements. The weights are adjusted based on a comparison of ANN output and the target, until they match. ANNs have an advantage over deterministic models in that the data needs are usually less and they are well suited for long-term forecasting. The disadvantage of the ANN is that it is based on a 'black box' approach since the internal structure of the model is generally not known and must be developed by a trial and error process. There has been a growing trend for the use of ANNs in the areas of hydrologic and water quality modeling Sharma *et al*. (2003),Yu *et al*. (2004),ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000),Sudheer and Jain (2003); Maier and Dandy (2000), and land drainage engineeringYang *et al*. (1996).Despite the black-box nature of the ANN, it has the flexibility in inclusion of parameters and in capturing the non-linearity of rainfall-runoff-sediment yield processes, making it more attractive for modeling hydrological processesCoulibaly *et al*. (2000). The main advantage of the ANN approach over traditional methods is that it does not require an explicit description of the complex nature of the underlying process in a mathematical formNayak *et al*. (2005). Cannon and Whitfield (2002)suggested ANNs to be superior to stepwise linear regression procedures while conducting a study on predicting runoff from 5-day mean stream flow atmospheric data from 21 watersheds of British Columbia, Canada. Bhattacharya *et al*. (2005)sed a feed-forward three-layer back propagation (BP) ANN model to predict the sediment concentration in rivers using eight input parameters reflecting sediment and riverbed information. The ANN approach provided better results than other formulas used for estimation of sediment concentration. Sudheer *et al*. (2002)196 A. Sarangi, A.K. Bhattacharya / Agricultural Water Management 78 (2005) 195–208 developed a new approach for designing the network structure in an ANN-based rainfall-runoff model. The method used the statistical properties, such as an autocorrelation function and a partial autocorrelation function of the data series in identifying a unique input vector that best represented the process for the basin, and a standard algorithm for training.

2. Previous Research:

The assessment of the volume of sediment being transported by a river is of particular interest in hydraulic engineering due to its importance in the design and management of water resources projects. The prediction of river sediment load constitutes an important issue in hydraulic and sanitary engineering. In reservoir design, a "dead storage" volume is meant to accommodate the sediment income that will accumulate over the "economic life". The underestimation of sediment yield results in insufficient reservoir capacity while overestimation leads to over-capacity reservoirs. Appropriate reservoir design and operation justify every effort to determine sediment yield accurately, but in environmental engineering the prediction of river sediment load has an additional significance, especially if the particles also transport pollutants.A number of attempts have been made to relate the amount of sediment transported by a river to flow conditions such as discharge, velocity and shear stress. However, none of the equations derived have received universal acceptance. Usually, either the weight or the concentration of sediment is related to the discharge. These two forms are often used interchangeably McBean (1988) examined this issue and concluded that the practice of using sediment load *vs* discharge is misleading because the goodness of fit implied by this relationship is spurious. Instead they recommended that the regression link be established. The physically-based models are based on the simplified partial differential equations of flow and sediment flux as well as on some unrealistic simplifying assumptions for flow and empirical relationships for erosive effects of rainfall and flow. Examples of such models are presented by Wicks and Bathurst (1996), Refsgaard (1997) and others.These highly sophisticated and complex models have components that correspond to physical processes. They are theoretically capable of accounting the spatial variation of catchment properties as well as uneven distribution of precipitation and evapotranspiration.The model complexity should, however, be keyed to utilizable information about the catchment characteristics and density and frequency of the available input data. Inparticular, because the real spatial distribution of precipitation is not presently measurable for much of the world, process-oriented distributed models offer no practical advantage over lumped models and have many disadvantages Aytek and Kisi (2008).Neural networks (NN) have been successfully applied in a number of diverse fields including water resources. In the hydrological forecasting context, artificial neural networks (ANNs) may offer a promising alternative for rainfall–runoff modelling Shamseldin (1997),Tokar and Johnson (1999), Wilby *et al*. (2003), Solomatine and Dulal (2003)), streamflow prediction Clair and Ehrman (1998); Pang *et al*. (2002),Shivakumar *et al*. (2002),Cigizoglu (2003) ;Chibanga *et al.*, 2003; Kisi, 2004a;Kerem Cigizoglu and Kisi (2006) and reservoir inflow forecasting . There are few published works in the field of suspended sediment data prediction using artificial intelligence methods such as neural networks and fuzzy logic approach Alp and Cigizoglu (2007),Tayfur (2002), Kisi (2006)). reviewed the ANN-based modelling in hydrology over the last years, and reported that about 90% of the experiments extensively make use of the multi-layer feed-forward neural networks (FNN) trained by the standard backpropagation (BP) algorithm. Maier & Dandy (2000) reviewed 43 papers dealing with the use of the ANN model for the prediction and forecasting of water resources variables. They reported that in 41 papers multi-layer perceptron (MLP) neural networks with gradient descent algorithm were used. Since they often yield sub-optimal solutions El-Bakry (2003)), a more powerful MLP learning algorithm, that is, the Levenberg-Marquardt algorithm is used for all applications in this study.

3. Methodology:

3.1. Artificial Neural Network Model (ANN):

There is no standard rule to define the network structure. In this study the selection of the optimum network structure was performed by trial and error. Multilayer networks using the backpropagation algorithm were selected to construct this network. A basic neural model can be characterized by the functional descriptions of the connection network and the network activation (Equation 1).

$$S_j = \sum_{i=0}^{n=0} w_{ji} \times x_i \tag{1}$$

Each node j receives incoming signals from every node i in the previous layer. Associated with each incoming signal (x_i) is a weight (w_{ji}). The effective incoming signal (S_j) to node j is the weighted sum of all the incoming signals. The effective incoming signal, S_j, is passed through a nonlinear activation function (sometimes called a transfer function or threshold function) to produce the outgoing signal of the node. The transfer function, which is sigmoid function in this study as shown in Equation 2.

$$Y_j = f\left(s_j\right) = \frac{1}{1+\exp\left(-s_j\right)} \tag{2}$$

where S_j can vary on the range, but y_j is bounded between 0 and 1.The Levenberg-Marquardt (LM) training algorithm was used for the training purpose. The hidden layer started with a small number of neurons and increased progressively until the optimum structure was reached. Using optimum network architecture, the ANN model was trained for given inputs and output sets.

3.2. Improving the Model Generalization:

One of the problems that occur during neural network training is over fitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations. Early stopping technique was used to improve the model generalization; LM training algorithm, which converges too rapidly, was used. The training parameters were adjusted so that the convergence is relatively slow. The model parameters, Marquardt adjustment (mu), decreased factor for mu (mu-dec) and Increase factor for mu (mu_inc) were adjusted to the values that gave the best results.

3.3. Post Training Analysis:

The performance of a trained network can be measured to some extent by the errors on the training and test sets. But it is often useful to investigate the network response in more details. To perform this, a regression analysis between the network output and the corresponding targets were conducted to determine the slope and correlation coefficient. The statistical criteria used to evaluate the model performance were mean square error (MSE), mean absolute error (MAE), Theil's coefficient (U), and correlation coefficient (R). T-test with 95% confidence for comparing the means of observed and simulated data was examined. These criteria were employed to measure the goodness of fit of the model and used to test the model efficiency in both training and testing phases. Final weights and bias values calculated during training phase for the network were used in the testing phase. The validation involves evaluating the network performance on a set of test problems that were not used for training. The model output from the testing phase was compared to the observed data and examined using the same statistical criteria that was used during the training phase to evaluate the model performance with a data that was never seen by the model during the training stage.

3.4 Multi-layer perceptrons:

An MLP distinguishes itself by the presence of one or more hidden layers, with computation nodes called hidden neurons, whose function is to intervene between the external input and the network output in a useful manner. By adding hidden layer3, the network is enabled to extract higher-order statistics. In a rather loose sense, the network acquires a global perspective despite its local connectivity due to the extra set of synaptic connections and the extra dimension of NN interconnections.

3.5 Model Evaluation:

The model efficiency factor (E), coefficient of determination (CR) . where CR is the Nash-Sutcliffe efficiency used for evaluating the ability of reproducing the time evolution of stream flows, CR below zero indicates that average measured sediment would have been as good a predictor as the modeled sediment flow.eq3.

$$CR = 1 - \frac{\sum_{i=1}^{N}\left(Qs_i - Qo_i\right)^2}{\sum_{i=1}^{N}\left(Qo_i - \overline{Qo}\right)^2} \tag{3}$$

3.6. Study Area:

The study area is sorkeab river one of sub catchments of DEZ watershed and includes This sub watershed is located between latitudes 33º 04'', 33º 14'' N and longitudes (UTM zone)48º 23'' ,48º 40''. Sorkhab river is in basin outlet.

Table 1: Stats of kesvar station

Base Statically for station data's of Keshvar					
MIN	MAX	VARIANCE	STANDARD DEVIATION	AVERAGE	DISCHARGE
0.005	147	654.90	25.59	18.71	$Q_w(m^3/s)$
0.001	7o713	12734006.48	11283.35	5533.71	Qs(ton/day)

Table 2: Impact of Data's logarithmic on network

Network Type	Decoration	Data type	correlation Coefficient of training	correlation Coefficient of health	Training error
FFBP	1-3-1	Non-logarithmic	0.7237	0.6951	0.0094
FFBP	1-9-1	Non-logarithmic	0.6967.	0.7578	0.0084
FFBP	1-15-1	Non-logarithmic	0.8205	0.5296	0.0065
FFBP	1-3-1	logarithmic	0.9486	0.9355	0.0025
FFBP	1-9-1	logarithmic	0.9538	0.9283	0.0022
FFBP	1-15-1	logarithmic	0.9543	0.9173	0.0022

RESULTS AND DISSCUSION

4.1.Testing Association of:

A difficult task with the MLP method is choosing the number of hidden nodes. There is no theory yet to tell how many hidden units are needed to approximate any given function. The network geometry is problem dependent. Here, the three-layer MLP with one hidden layer is used and the common trial-and-error method is used to select the number of hidden nodes.Before applying the MLP method, the input data were normalized to fall in the range [0, 1]. The river flow Q was standardized by the following formula:$Qs = Q/Q\max$ where Qs is standardized flow; and Qmax is the maximum of the flow values. The sediment concentration data were also standardized in a similar way. These normalized data were used to train each of the ANN models. After training was over, the weights were saved and used to test (validate) each network performance on test data. The ANN results were transformed back to the original domain, and the mean root square error (*MRSE*) and mean absolute error (*MAE*) were computed using test data for each of the ANN models. The *MRSE* and *MAE* are denoted as:The comparison between simulated results and the observed data was evaluated statistically. The criteria to evaluate the agreement between simulated data and measured data are namely, mean absolute error (MAE), root mean square error (RMSE), Theil's inequality coefficient (U), coefficient of determination (R^2) and the coefficient of efficiency (E). The MAE, RMSE and U criteria can be determined from the Equations 4,5 and 6:

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - A_i)^2} \tag{4}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| P_i - A_i \right| \tag{5}$$

$$U = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - A_i)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i)^2} + \sqrt{\frac{1}{n} \sum_{i=1}^{n} (A_i)^2}} \tag{6}$$

Where P_i = the predicted data from the model, A_i = the experimental data and n = the number of records, (DehghaniSanij *et al*. (2004)). The MAE, MSE statistics have as the lower limit, the value of zero, which is the optimum value for them as it is for this study.

Table 3: Impact of using of middle layers on network results

Network Type	Decoration	Data type	correlation Coefficient of training	correlation Coefficient of health	Training error
FFBP	1-12-1	Lm	0.9536	0.9400	0.0022
FFBP	1-7-8-1	Lm	0,9567	0.9367	0.0021
FFBP	1-7-8-11	Lm	0.9615	0.9071	0.0019

4.2. Multiple Regression:

The multiple linear regression model is an extension of a simple linear regression model to incorporate two or more explanatory variable in a prediction equation for a response variable. Multiple regression modeling is now a mainstay of statistical analysis in most fields because of it's power and flexibility For estimate very complicated models with large numbers of variables. Practical experience has shown however, that such models may be very hard to interpret and give very misleading impressions.

4.3. Derivation of Discharge-sediment Yield Curves:

One of the most important tasks in sediment transport is the derivation of the sediments. The estimation of those in a time step, is conducted based on the discharges, in every hydrological station given that recorded hydrometric measurements and cross sections in the water stage, are available. A general methodology was developed for the derivation o f multiple discharge-sediment yield curves in a river section. For this case relationship of regression between discharge and sediment is $Q_s = 39.87 Q_w^{1.473}$ and correlation Coefficient of training equal0.655 correlation Coefficient of heath equal 0.6375 figure1.

Table 4: Impact using of previous days discharges for estimation of sediment

Network Type	Decoration	Data type	input neuron	correlation Coefficient of training	correlation Coefficient of health	Training error	
FFBP	1-12-1	Lm	Q_n	0.9400	0.9536	0.0022	
FFBP	1-12-1	Lm	Q_{n-1}	0.8208	0.8291	0.0099	-
FFBP	1-12-1	Lm	Q_{n-2}	0.821	0.8257	0.0105	-
FFBP	1-12-1	Lm	Q_{n-3}	0.8165	0.8173	0.0110	-
FFBP	1-12-1	Lm	Q_{n-4}	0.7649	0.8072	0.0112	-
FFBP	1-12-1	Lm	Q_{n-5}	0.7572	0.7886	0.117	-
FFBP	2-6-1	Lm	Q_{n-6}	0.9375	0.9570	0.0021	0.0034
FFBP	3-4-1	Lm	Q_{n-7}	0.9376	0.9376	0.0020	-
FFBP	4-5-1	Lm	Q_{n-8}	0.9351	0.9613	0.0019	-
FFBP	5-4-1	Lm	Q_{n-9}	0.9413	0.9611	0.0019	-
FFBP	6-5-1	Lm	Q_{n-10}	0.8938	0.9641	0.0018	-

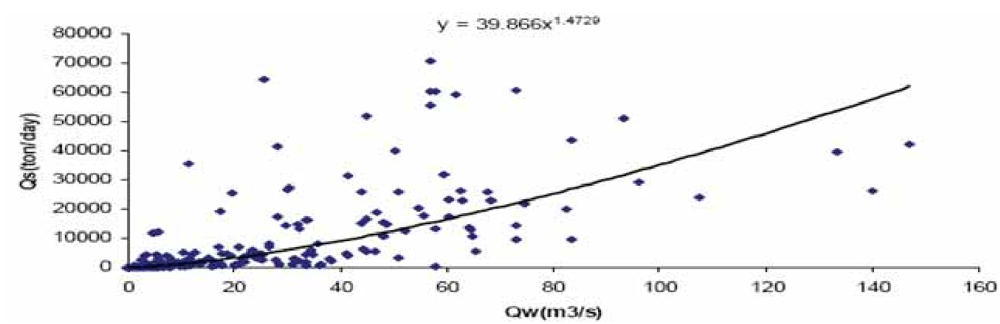

Fig. 1: Discharge-sediment curve station of keshvar

Table 5: Computed sediment of Keshavr station by using multi-regression linear and logarithmic

Mode1 input	multi-regression linear				multi-regression logarithmic			
	correlation Coefficient of training	correlation Coefficient of health	Training error	health error	correlation Coefficient of training	correlation Coefficient of health	Training error	health error
Q_n	0.6064	0.6812	0.0387	0.0414	0.9476	0.9364	0.4654	0.4449
Q_{n-1}	0.5449	0.5894	0,0351	0.0300	0.8051	0.9254.	0.4593	0.4208
Q_{n-2}	0.4692	0.5872	0.0336	0.0282	0.7939	0.9146	0.4588	0.4202
Q_{n-3}	0.4366	0.5573	0.0330	0.0273	0.7735	0.8948	0.4580	0.4190
Q_{n-4}	0.4240	0.5014	0.0328	0.0274	0.7616	0.8868	0.4576	0.0.4204
Q_{n-5}	0.3690	0.4790	0.0319	0.0278	0.7536	0.8713	0.4573	0.4196
Q_1 ,Q_{n-1}	0.6946	0.6819	0.0387	0.0415	0.9476	0.9364	0.4654	0.4449
Q_1 ,Q_{n-1},Q_{n-2}	0.7038	0.6678	0.0390	0.0426	0.9481	0.9367	0.4654	0.4461
Q_1 ,Q_{n-1},Q_{n-2},Q_{n3}	0.7070	0.6616	0.0391	0.0434	0.9491	0.9358	0.4655	0.4462
Q_1 ,Q_{n-1},Q_{n-2},$Q_{n-3}Q_{n-4}$	0.7079	0.6690	0.0399	0.0434	0.9493	0.9356	0.4655	0.4462
Q_1 ,Q_{n-1},Q_{n-2},Q_{n-3},Q_{n-4},Q_{n-5}	0.7344	0.6573	0.0391	0.0438	0.9510	0.9377	0.4656	0.4470

5. Conclusions:

In the present study, association of watershed morphological parameters with the runoff rate measured at the watershed outlet and feeding to a ANN -MLP with feed-forward Back propagation(FFBD) approach resulted in a better prediction of sediment load when compared with the recorded data of the study watershed and the results of an earlier regression approach for the same purpose. It is evident that the neural network and regression models developed for one watershed cannot be applied to watersheds at different location as such, and also the empirical association of geomorphological parameter with rainfall and runoff may differ from place to place. However, this study standardizes the ANN approaches, which can be applied to any watershed data for development of ANN models for subsequent prediction. The study results confirm that inclusion of morphological parameters in ANN models improves the model prediction. Results show that estimated rate of sediment yield by Artificial neural networks is much better fits with the observed data in comparison to MR model. So that the differences between the estimated and the measured amount of sediment yield were respectively for Artificial neural networks model.

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