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USING ARTIFICIAL NEURAL NETWORKS (ANNs) FOR SEDIMENT LOAD FORECASTING OF TALKHEROOD RIVER MOUTH

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Abstract: Without a doubt the carried sediment load by a river is the most important factor in creating and formation of the related Delta in the river mouth. Therefore, accurate forecasting of the river sediment load can play a significant role for study on the river Delta. However considering the complexity and non-linearity of the phenomenon, the classic experimental or physical-based approaches usually could not handle the problem so well. In this paper, Artificial Neural Network (ANN) as a non-linear black box interpolator tool is used for modeling suspended sediment load which discharges to the Talkherood river mouth, located in northern west Iran. For this purpose, observed time series of water discharge at current and previous time steps are used as the model input neurons and the model output neuron will be the forecasted sediment load at the current time step. In this way, various schemes of the ANN approach are examined in order to achieve the best network as well as the best architecture of the model. The obtained results are also compared with the results of two other classic methods (i.e., linear regression and rating curve methods) in order to approve the efficiency and ability of the proposed method.

Keywords: River mouth; River Delta; Sediment load; Black box modeling; Artificial neural networks

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INTRODUCTION

Erosion of rich fertile soil from the catchment areas and reduction in reservoir capacity, beside great impacts on creating and formation of the related Delta in the river mouth are some of the reasons that cause soil erosion in catchment areas and the subsequent deposition in rivers, lakes and reservoirs to be a great concern. Hence, recently researchers pay more attention to this complex problem because of its effects on the environments and biosystems and many mathematical models have been developed in order to simulate this complex process. Models based on their involvement of physical characteristics generally fall into three broad categories: black box or system theoretical models, conceptual models and physical based models (Nourani & Mano, 2007). In the cases with high rate of complexity which we can't consider every effective physical parameter, it is not surprising that black box models, which convert input variable values to output variable values in ways that have nothing to do with what happens in reality, may produce more accurate results than physical based models. One of black box modeling tools that lately found application in variety of areas including hydraulic and hydrology is Artificial Neural Network (ANN). ANN is a tool for nonlinear input-output mapping which is suited to complex nonlinear models and it has the ability to learn from examples without explicit physics. It usually produces results faster than its physical counterparts and as accurately or more so, but only within range of values observed in the data used to build the model (Nourani *et al.*, 2009a). ANN was developed in 1940s, but in recent years by improves in Information Technology (IT) and computer science, there is a great interest for its application in engineering modeling.

Tremendous ANN models have been developed and described for modeling runoff-sediment and rainfall-runoff-sediment yield as important hydrological processes. Jain (2001) used the ANN approach to establish an integrated stage-discharge-sediment concentration relation. Through his study, it has been shown that the ANN results are much closer to the observed values than the conventional technique. Nagy *et al.* (2002) presented a feed forward ANN model to estimate the natural sediment discharge in rivers so that the input parameters were reflecting sediment and river-bed information. They showed that the neural network models could be successfully applied for modeling sediment transport and by increasing the learning input patterns with a wide range of variables, the accuracy of the ANN estimated results should be increased. Flow and sediment transport in a river system were modeled utilizing ANN by Yitian & Gu (2003) and it was concluded that the ANN is a reliable model for describing flow and sediment transport process in a river system. Two different ANN algorithms with consideration of hydro-meteorological data were used sediment load. The simulations provided satisfactory results in terms of the selected performance criteria comparing well with conventional multi-linear regression. Agarwal *et al.* (2006) developed an Artificial Neural Network for estimation of runoff and sediment yield and showed that daily time unit performed well in both calibration and verification steps, and also pattern learning process of model building was superior to batch learning process. A neural network model, using a data-driven algorithm, was constructed by Kisi (2007) for estimating sediment discharge. He concluded that the statistical pre-processing of the data could significantly reduce the effort and computational time required in developing the ANN model. Rai & Mathur (2008) developed a feed forward back propagation artificial neural network for computation of event-based temporal variation of sediment yield from the watersheds.

Because of some financial and technical problems, the exact measurement of the sediment load is a very difficult matter in some developing courtiers such as Iran and usually only a few sediment data may be obtained from hydrometery stations of such countries during a month. In such a situation, a model which employs the available water discharge data in order to estimate the sediment load values can be a reliable choice. In contrary to the other developed models which usually use the previous time steps sediment data as the models input in addition to the water discharge, in this paper it is tried to present an ANN model which just uses water discharge data in the input layer. For this purpose, the data from Akhule station which is near to the Talkherood River Delta, Iran are employed. Furthermore, obtained results from this model are compared with the results of two conventional methods, sediment rating curve and linear regression.

ARTIFICIAL NEURAL NETWORKS (ANNS)

ANN is widely applied in the forecasting of hydrology and water resource variables. In ANN, BP network models are common to engineer. So called a BP network model, which is the feed-forward artificial neural network structure and a back-propagation algorithm (BP). It has proved that BP network model with three-layer is satisfied for the forecasting and simulating as a general approximator (Hornik *et al.*, 1989). Thus, a three layer BP network model trained by Levenberg-Marquardt optimization algorithm is chosen for this study.

As shown in **Fig. 1**, three-layered feed forward neural networks (FFNNs), which have been usually used in forecasting hydrologic time series, provide a general framework for representing nonlinear functional mapping between a set of input variables and the output. Three-layered FFNNs are based on a linear combination

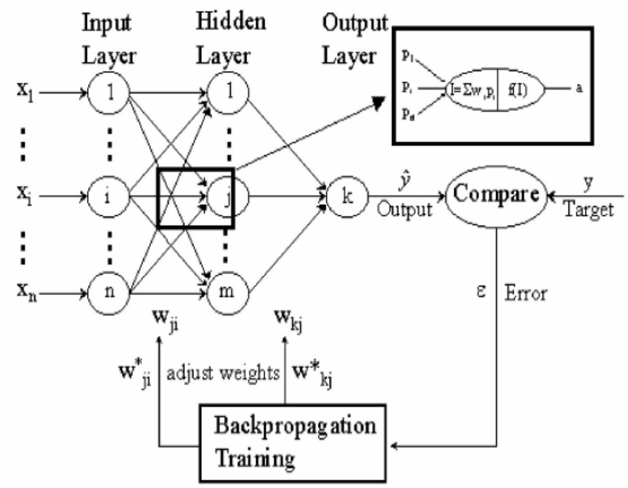


Fig. 1 A three layered FFNN with BP training algorithm.

nonlinear activation function. In the **Fig. 1** *i*, *j* and *k* denote input layer, hidden layer and output layer neurons, respectively and *w* is the applied weight of the neuron. The term "feed-forward" means that a neuron connection only exists from a neuron in the input layer to other neurons in the hidden layer or from a neuron in the hidden layer to neurons in the output layer and the neurons within a layer are not interconnected to each other.

The explicit expression for an output value of FFNNs is given by (Kim & Valdes 2003):

$$\hat{y}_k = f_o\left[\sum_{j=1}^{m} w_{kj}.f_h\left(\sum_{i=1}^{n} w_{ji}x_i + w_{jo}\right) + w_{ko}\right] \quad (1)$$

where w_{ji} is a weight in the hidden layer connecting the *i*-th neuron in the input layer and the *j*-th neuron in the hidden layer, w_{jo} is the bias for the *j*-th hidden neuron, f_h is the activation function of the hidden neuron, w_{kj} is a weight in the output layer connecting the *j*-th neuron in the hidden layer and the *k*-th neuron in the output layer, w_{ko} is the bias for the *k*-th output neuron, f_o is the activation function for the output neuron, x_i is *i*-th input variable for input layer and $\hat{y}$, y are computed and observed output variables. The *n* and *m* respectively are the number of neurons in input and hidden layers. The weights are different in the hidden and output layers, and their values can be changed during the process of network training. According to the mentioned concept a computational code has been developed by the author in order to do any related hydrological modeling.

STUDY AREA AND DATA

The data used in this study are from Akhule hydrometric station on the Talkherood River which is the closest station to the river Delta connected to Urmieh Lake which is the second saltiest lake in the world. The Talkherood River contains high level of sediment and salinity and its watershed is located in northwest Iran at Azarbayjan province and east of Urmieh Lake (between 37°24' and 38°37' North latitude and 45°30'and 47°45' East longitude). **Figure 2** shows the map of study area. Talkherood River passing through a valley between West Arasbaran, Ghoushdagh and Sabalan mountains at north and Bozgoush and Sahand Mountains at south discharges to Urmieh Lake.

For most of its course, the river flows east to west. The length of river reaching Urmieh Lake's Delta is about 276 km and the watershed's area is near 13 853 km^2. Watershed elevation is varying between 1280 m to 3620 m above sea level. Watershed contains moderate to medium vegetative cover as a rural region and the geology formation is hard volcanic and the topography is steep. The prevailing climate of the study area is snowy and sub-humid. The mean daily temperature vary from -22°C in January up to 40°C in July with a yearly average of 9°C. The mean yearly precipitation is about 400 mm. Daily discharge data are through 2002 to 2005 for Akhule station but suspended sediment data are very sparse and rare at the same time period. About 380 sediment measurements have been recorded for this period and are used in this study. The daily runoff time series for 4 years is presented in **Fig. 3**. The data divided into two sets: the first 75% of total data (3 years) were used as calibrating or training set and the second 25% (1 year) were used for the model verification.

Utilizing **Eq. 2**, the used data in modeling were normalized between 0 and 1 before entering to the ANN model.

$$r_i = \frac{R_i - R_{min}}{R_{max} - R_{min}} \quad (2)$$

where R_i is the actual value, r_i is the respective normalized value, $R_{\min}$ and $R_{\max}$ are the minimum and maximum of all the used values, respectively.

RESULTS AND DISCUSSION

Identifying the architecture of the used ANN for modeling runoff-sediment yield process is primary and important aspect of the modeling. In this study considering previous research (Rajaee *et al.*, 2009), some parts of network, e.g. number of hidden layers (one layer), learning rate (α = 0.6), activation function (tansig) and number of output layer neurons (just one), were assumed as the constant and on the other hand, some other parts, e.g. number of the neurons in input and hidden layers and number of training epochs, are counted as dynamic parameters which must be optimized through a trial-error process. The number of neurons in input layer varies from 1 to 3 which represents the amount of water discharge (Q_{t-i}) at the current day, one day (Q_{Wt-1}) and two days (Q_{Wt-2}) before the date of observed sediment load (Q_{st}) data. Number of hidden layer's neurons varies from 2 to 10. Using available data of the study watershed, the network architecture that yielded the best results in terms of determination coefficient (**Eq. 3**) (Nourani *et al*., 2009b) on the training (using training data set) and verifying (using verifying data set) steps, determined through trial and error process.

$$E = 1 - \frac{\sum_{i=1}^{N} \left(Q_i - \hat{Q}_i\right)^2}{\sum_{i=1}^{N} \left(\hat{Q}_i - \hat{Q}\right)^2} \qquad (3)$$

where E, N, $\hat{Q}_i$, Q_i and $\hat{Q}$ are respectively determination coefficient, number of observations, observed data, predicted values and mean of observed data. **Table 1** presents the E for both calibration and verification stages of different ANN structures and efficient epoch applied for the same data sets. Considering these results, 3.6.1 structure (i.e., respectively 3, 6 and 1 neurons in input, hidden and output layers) is the suitable one in comparison with other used ANN structures, that leads to considerable calibration and verification E. To prove the efficiency of selected ANN model, the obtained results were compared with the results of two other classical models, sediment rating curve (SRC) and linear regression.

A rating curve is a power-law formula which relates sediment discharge or concentration (Q_S) to the stream discharge (Q_W), and can be used to estimate sediment loads from the stream flow record (Cobaner *et al*., 2009), as:

$$Q_s = aQ_W{}^b \qquad (4)$$

Applying the used normalized training data set, values of a and b were calibrated as 1.346 and 1.72, respectively (**Fig. 4**), then the obtained formula was verified using verifying dada set. The values of E for calibration and verification steps were 0.885 and 0.7, respectively.

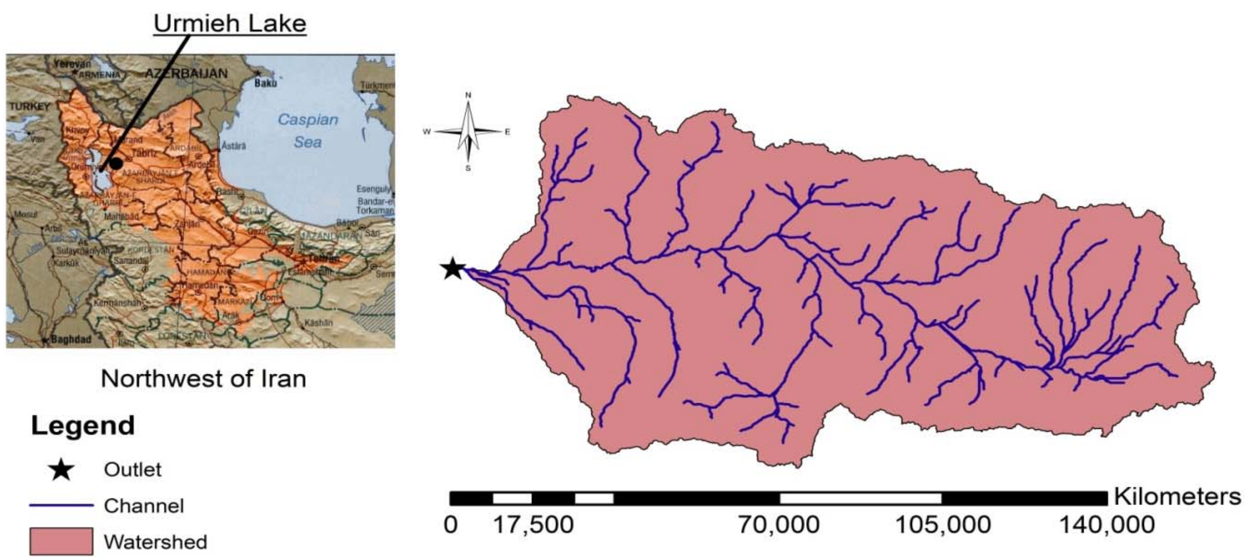


Fig. 2 Study area.

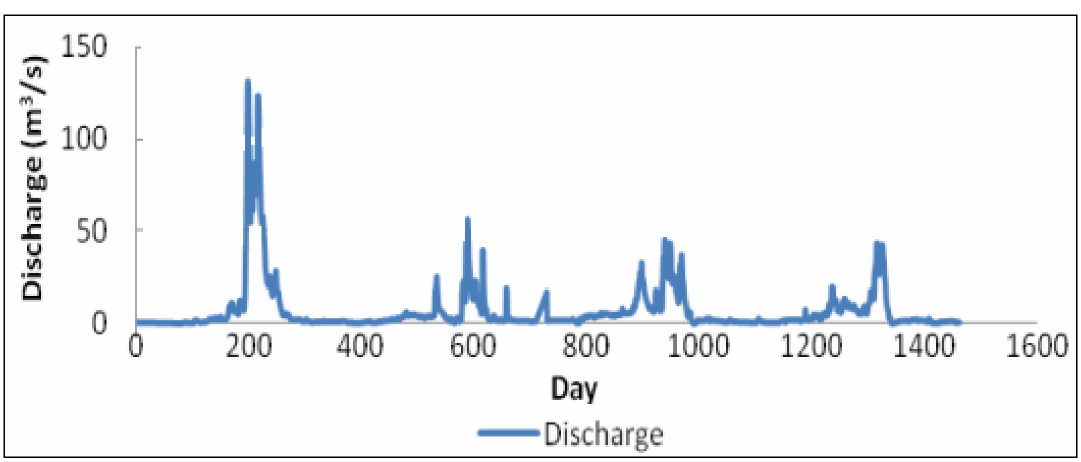
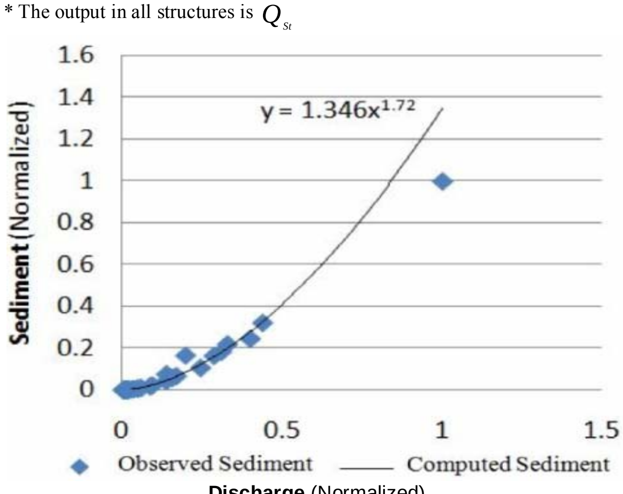


Table 1. Structure and performance of the used ANNs

Structure	Input *	Epoch	*E*-Calibration	*E*-Verification
1.2.1	Q_{Wt}	36	0.973	0.878
1.3.1	Q_{Wt}	30	0.973	0.878
1.4.1	Q_{Wt}	26	0.973	0.878
1.5.1	Q_{Wt}	28	0.973	0.869
1.6.1	Q_{Wt}	28	0.961	0.834
1.7.1	Q_{Wt}	30	0.973	0.878
1.8.1	Q_{Wt}	30	0.952	0.833
1.9.1	Q_{Wt}	28	0.973	0.878
1.10.1	Q_{Wt}	30	0.973	0.877
2.2.1	Q_{Wt}, Q_{Wt-1}	24	0.973	0.900
2.3.1	Q_{Wt}, Q_{Wt-1}	38	0.973	0.881
2.4.1	Q_{Wt}, Q_{Wt-1}	26	0.973	0.862
2.5.1	Q_{Wt}, Q_{Wt-1}	26	0.973	0.863
2.6.1	Q_{Wt}, Q_{Wt-1}	24	0.972	0.874
2.7.1	Q_{Wt}, Q_{Wt-1}	24	0.973	0.858
2.8.1	Q_{Wt}, Q_{Wt-1}	36	0.975	0.916
2.9.1	Q_{Wt}, Q_{Wt-1}	28	0.973	0.878
2.10.1	Q_{Wt}, Q_{Wt-1}	24	0.973	0.869
3.2.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	46	0.977	0.886
3.3.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	50	0.980	0.925
3.4.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	46	0.978	0.922
3.5.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	50	0.980	0.912
3.6.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	***34***	***0.979***	***0.935***
3.7.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	56	0.980	0.913
3.8.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	30	0.977	0.865
3.9.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	34	0.977	0.875
3.10.1	$Q_{Wt}, Q_{Wt-1}, Q_{Wt-2}$	36	0.977	0.898

* The output in all structures is Q_{St}



The other classical method, proposed for comparison, was linear regression that considers a linear relation between Q_{Wt}, $Q_{Wt\text{-}1}$, $Q_{Wt\text{-}2}$ and Q_{St}. The parameters of the model were estimated by the Minimum Least Squared Error method. The corresponding equation which yielded to the best performance in both calibration and verification steps is as:

$$Q_{St}=0.547Q_{Wt}+0.5Q_{Wt-1}-0.109Q_{Wt-2}-0.028 \quad (5)$$

The related values of *E* are 0.967 and 0.747, although the calibration value of *E* is appropriate, it didn't work well in verification. **Figure 5** presents a scatter plot between observed and computed sediment

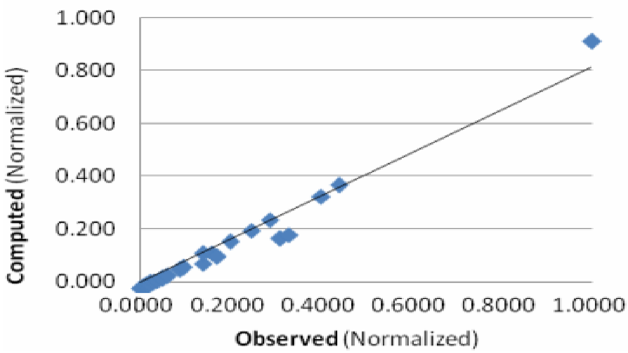


Fig. 5 Scatter plot for observed and computed sediment using linear regression.

Table 2 shows the values of *E* for the three methods. Through examining this table, it is obvious that ANN could perform better and present proper *E* values for both calibration and verification steps. Since linear regression model has four parameters for calibration, its performance is much better than the rating curve method. Furthermore, rating curve uses all of the data in a lumped form without considering time sequence effect in the calibration. However, sediment-discharge process usually behaviors as a Markov chain process, so that the value of the parameter in the current time may be related to the previous time steps conditions.

CONCLUSIONS

In this study, there was an endeavor to determine a suitable architecture of ANN model and indicate the performance of ANN's application to problems concerning the estimation of sediment load from runoff, comparing with two conventional methods. It was found that an ANN model with three neurons in input layer, representing the quantity of discharge at the current day, one day and two days before the date of observed suspended sediment load data and six neurons in hidden layer, offers the most promising results compared to the other methods. It should be mentioned that application of wide range of well-established data may lead to an increase in the accuracy of the ANN results.

As a suggestion for the future research and in order to complete the presented study, the output of the developed ANN model can be linked to a two or three dimensional hydraulic model for routing the sediment load over the river Delta and determine the probable form variations of the Delta.

Table 2. Results of the models

Method	*E*-Calibration	*E*-Verification	Formula
Linear Regression	0.967	0.747	$Q_{St}=0.547Q_{Wt}+0.5Q_{Wt-1}-0.109Q_{Wt-2}-0.028$
Rating Curve	0.885	0.7	$Q_S=1.346Q_W^{1.72}$
ANN	0.979	0.935	3.6.1, 34 Epochs

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