

Suspended Sediment Estimation Using an Artificial Intelligence Approach

Mustafa Demirci, Fatih Üneş and Sebahattin Saydemir

Abstract Forecasting of sediment concentration in rivers is a very important process for water resources assignment development and management. In this paper, a neural network approach is proposed to predict suspended sediment concentration from streamflow. A comparison was performed between artificial neural network, sediment rating-curve and multilinear regression models. It was based on a 5 years period of continuous streamflow, suspended sediment concentration and mean water temperature data of West Virginia, Little Coal River, Danville station operated by the United States Geological Survey. Based on comparison of the results, it is found that the artificial neural network model gives better estimates than the sediment rating-curve and multilinear regression techniques.

Keywords Suspended sediment · Forecasting · Neural network · Sediment rating curve · Multi-linear regression

1 Introduction

The assessment of the volume of sediment transported by a river is of vital 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. 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. Sediment rating curves are largely used to estimate the sediment transport in river. However, traditional sediment rating curves are not able to provide sufficiently accurate results. A sediment rating curve is a relation between the sediment and

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river discharges. Such a relationship is usually established by a regression analysis, and the curves are generally expressed in the form of a power equation. McBean and Al-Nassri (1988), investigated suspended sediment rating curves and the practice of using sediment load versus discharge is shown to be misleading, since the goodness of fit implied by this relation is spurious.

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. Artificial Neural Networks (ANNs) are gaining popularity, especially over the last few years, in terms of hydrological applications. In the hydrological forecasting context, recent experiments have reported that ANNs may offer a promising alternative for rainfall–runoff modelling (Sudheer et al. 2002; Wilby et al. 2003; Solomatine and Dulal 2003), streamflow prediction (Raman and Sunilkumar 1995; Zealand et al. 1999; Chibanga et al. 2003; Cigizoglu 2003; Kisi 2004a; Cigizoglu and Kisi 2005) and reservoir inflow forecasting (Saad et al. 1996; Jain et al. 1999). Üneş (2010b) developed an ANN model for dam reservoir level estimation. Toprak and Cigizoglu (2008) used ANN for predicting longitudinal dispersion coefficient in natural streams. Üneş (2010a) predicted density flow plunging depth in dam reservoir using the ANN. The last decade has witnessed a few applications of the artificial intelligence techniques in water resources forecasting (Hundecha et al. 2001; Tayfur 2002; Tayfur et al. 2003; Kisi 2004b). To the knowledge of the author, no work has been reported in the literature that addresses the application of the neuro-fuzzy approach for the estimation of suspended sediment. This provided an impetus for the present investigation. Jain et al. (1999) used a single ANN approach to establish sediment-discharge relationship and found that the ANN model could perform better than the rating curve. Tayfur (2002) developed an ANN model for sheet sediment transport and indicated that the ANN could perform as well as, in some cases better than, the physically-based models. Cigizoglu (2004) investigated the accuracy of a single ANN in estimation and forecasting of daily suspended sediment data. Kisi (2004c) used different ANN techniques for daily suspended sediment concentration prediction and estimation and he indicated that multi-layer perceptron could show better performance than the others. Kisi (2005) developed an ANN model for modeling suspended sediment and compared the ANN results with those of the rating curve and multilinear regression. Cigizoglu and Kisi (2006) developed some methods to improve ANN performance in suspended sediment estimation. Lohani et al. (2007), evaluated the performance of the conventional sediment rating curves, neural networks and fuzzy rule-based models using the coefficient of correlation, root mean square error and pooled average relative (underestimation and overestimation) errors (PARE) of sediment concentration. Demirci and Baltaci (2012), proposed a fuzzy logic approach to estimate suspended sediment concentration from streamflow. It was found that the fuzzy logic model gave better estimates than the other techniques.

In Lopes and Ffolliott (1993), data from a 455-acre clear-cut ponderosa pine forest watershed in northern Arizona were used to identify relationships between suspended sediment concentration and streamflow discharge. Scatter about the

straight line relationship was found when all available pairs of suspended-sediment-concentration and streamflow measurements were used together. The effect of some of the variation was offset by subdividing the data set on the basis of streamflow generation mechanisms.

The main aim of this study is to analyze the performances of an adaptive ANN computing technique for daily sediment estimation. This study is concerned with the application of neural network for modeling suspended sediment concentration. This logic is used to develop discharge–sediment rating curves. The daily streamflow, temperature and suspended sediment time series data belonging to one station in USA are used.

2 Neural Networks

2.1 Artificial Neural Network

Artificial neural networks (ANNs) are based on the present understanding of the biological nervous system, though much of the biological detail is neglected. ANNs are massively parallel systems composed of many processing elements connected by links of variable weights. Of the many ANN paradigms, the back propagation network is by far the most popular (Lippman 1987). The network consists of layers of parallel processing elements, called neurons, with each layer being fully connected to the proceeding layer by interconnection strengths, or weights (W). Figure 1 illustrates a three-layer neural network consisting of layers i , j and k , with the interconnection weights W_{ij} and W_{jk} between layers of neurons. Initial estimated weight values are progressively corrected during a training process that compares predicted outputs to known outputs, and back propagates any errors (from right to left in Fig. 1) to determine the appropriate weight adjustments necessary to minimize the errors. The methodology used here for adjusting the weights is called “momentum back propagation”, and is based on the “generalized delta rule”, as

Fig. 1 An ANN architecture used for suspended sediment estimation (ref)

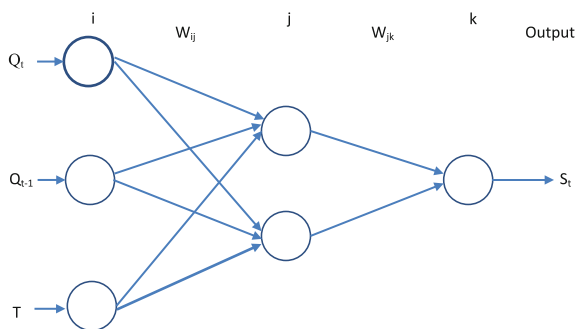
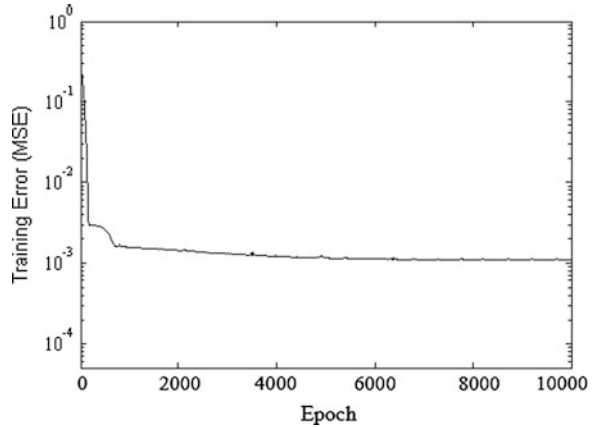


Fig. 2 The training error graph for the ANN model; training error, +: epoch (ref)



presented by Rumelhart et al. (1986). Throughout all ANN simulations, the adaptive learning rates were used for increasing the convergence velocity. The sigmoid and linear functions are used for the activation functions of the hidden and output nodes, respectively. The hidden layer node numbers of each model were determined after trying various network structures, since there is no theory yet to tell how many hidden units are needed to approximate a given function. The training of the ANN networks was stopped after 10,000 cycles, when the variation of error became sufficiently small. The error graph for an ANN model during training is shown in Fig. 2.

2.2 Sediment Rating Curves (SRC)

In the absence of manpower or automatic apparatus for frequent sampling, and laboratory facilities for analysis of numerous samples, many workers have utilized the rating-curve technique to estimate suspended sediment loads. A rating curve consists of a graph or equation relating sediment discharge or concentration to discharge, which can be used to estimate sediment loads from the streamflow record. The sediment rating curve generally represents a functional relationship of the form

$$S = aQ^b \quad (1)$$

in which Q is stream discharge and S is either suspended sediment concentration or yield. Values of a and b for a particular stream are determined from data via a linear regression between $(\log S)$ and $(\log Q)$. Equation (1) is usually combined with a streamflow duration curve to estimate the mean annual yield (Piest and Miller (1975)). A study by Campbell and Bauder (1940) on the Red River in Texas

provides an early documented example of the use of sediment rating curves in the USA. They developed a ‘silt rating curve’ by plotting daily suspended sediment load against daily river flow on logarithmic coordinates.

2.3 Multi-linear Regression (MLR)

If it is assumed that the dependent variable Y is effected by m independent variables X_1, X_2, \dots, X_m and a linear equation is selected for the relationship between them, the regression equation of Y can be written as:

$$y = a + b_1x_1 + b_2x_2 + \dots + b_mx_m \quad (2)$$

y in this equation shows the expected value of the variable Y when the independent variables take the values $X_1 = x_1, X_2 = x_2, \dots, X_m = x_m$.

The regression coefficients a, b_1, b_2, \dots, b_m are evaluated, similar to simple regression, by minimizing the sum of the e_{y_i} distances of observation points from the plane expressed by the regression equation (Bayazit and Oguz 1998).

$$\sum_{i=1}^N e_{y_i}^2 = \sum_{i=1}^N (y_i - a - b_1x_{i1} - b_2x_{i2} - \dots - b_mx_{im})^2 \quad (3)$$

In this study, the coefficients a, b_1, b_2, \dots, b_m are determined using least squares method.

3 Application and Results

The time-series data of Little Coal River, Danville Station located at West Virginia (USGS Station No. 03199000, latitude 38°04'47", longitude 81°50'11"), operated by the USGS were used in the study. The location of the station is shown in Fig. 3. The drainage area at this site is 697,000 km². The gauge datum is 201 m above sea level. For this station, daily time-series of river flow, suspended sediment concentration and mean water temperature were downloaded from the USGS Web server.

The statistical parameters of streamflow, suspended sediment concentration, temperature data of Little Coal River station are shown in Table 1. In this table, $S_x, C_{sx}, X_{max}, X_{min}, X_{ort}$ denote the standard deviation, the skewness coefficient, maximum, minimum and mean values. It can be seen from Table 1 that the S_x and C_{sx} coefficients for both the training and the testing period are very high. This shows the complexity of the streamflow—sediment interaction.



Fig. 3 The location of the Little Coal River, Danville station at West Virginia (USGS station no. 03199000)

Table 1 The statistical parameters of Little Coal River Danville station data

	Variables	T_{Max} (°C)	T_{Min} (°C)	T_{ort} (°C)	Q_s (m ³ /s)	S (mg/L)
Training period	x_{max}	34.50	27.00	30.50	365.29	2,990.00
	x_{min}	0.50	0.50	0.50	0.42	0.00
	X_{mean}	15.74	12.92	14.33	9.25	82.62
	s_x	9.16	7.74	8.42	18.23	195.91
	c_{sx}	0.01	-0.04	-0.03	10.92	6.67
Testing period	x_{max}	30.50	26.00	28.25	222.85	2,090.00
	x_{min}	1.00	0.50	0.75	0.91	0.00
	x_{ort}	14.72	12.60	13.66	15.45	127.19
	s_x	7.94	7.19	7.54	21.33	219.20
	c_{sx}	0.06	0.04	0.05	4.58	3.96

T_{Max} Maximum temperature; T_{Min} Minimum temperature; T_{ort} Mean temperature; Q_s Mean streamflow; S Mean suspended sediment concentration

The input combinations used in this application to estimate suspended sediment values for Little Coal River station are (i) Q_t ; (ii) Q_{t-1} ; (iii) T_{ort} ; where Q_t and T_{ort} represent, respectively, the streamflow and mean temperature at day t .

For 5 years data, results of modeling SRC, MLR, and ANN are shown as follows. For each model the minimum mean squared error (MSE), the total squared error (MAE) and correlation coefficients (R) are calculated between model predictions and observed values is calculated. Results are used to compare the performance of the model prediction and observation data. MSE and MAE was determined as follows:

$$\text{MSE} = \frac{1}{N} \left(\sum_{i=1}^N Y_{i\text{observed}} - Y_{i\text{forecast}} \right)^2 \quad (4)$$

and

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^N |Y_{i\text{observed}} - Y_{i\text{forecast}}| \quad (5)$$

where N is the number of data sets and Y_i sediment concentration data.

Using the data of mean water temperature, daily real-time streamflow and sediment concentration in the Little Coal River station, the best model was investigated and comparisons were made with the better results. As data for this study, 5 year data belonging to Little Coal River station has been used. With the using the 1827 data between 01 December 1975 until 01 December 1980, models are generated.

3.1 SRC Model Results

In Sediment rating curve (SRC) model, 1096 of 1827 data for the training, 731 data are divided for testing. Sediment rating curve for the training data (SRC) is shown in Fig. 4. The obtained sediment concentration data are compared with testing data and scatter plot is shown in Fig. 5.

In Fig. 5, the correlation coefficient was obtained as $R = 0.785$. In the test phase, sediment rating curve (SRC) is obtained and suspended sediment concentration scatter graph is shown. Values of sediment rating curve are seen to be spaced out from the actual values. The observed values are shown to be scattered for the results of the SRC for training data in Fig. 6 and for testing data in Fig. 7.

When scatter graphs for training and testing data are analyzed, SRC sediment concentration values show deviations between estimated values and the actual values. SRC values for training data are lower than the values given by the actual testing data values, SRC values for testing data are higher than the estimated values.

Fig. 4 Sediment rating curve for the training data (SRC)

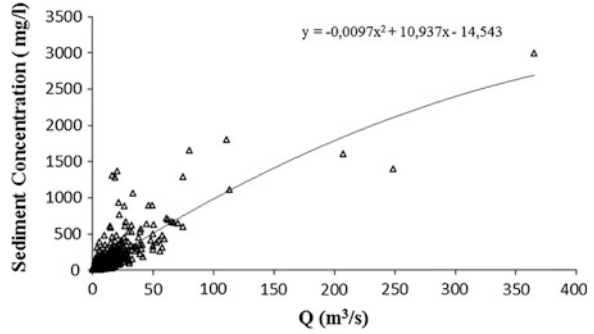


Fig. 5 SRC scatter graph for the observed data

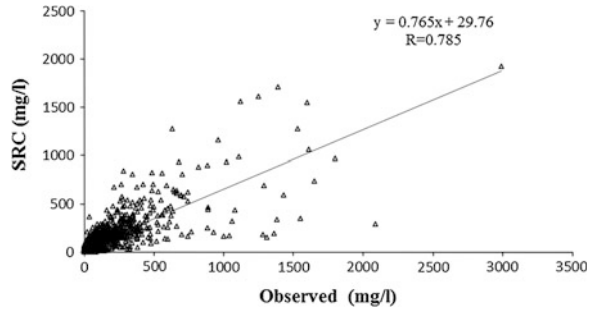


Fig. 6 Observed and SRC distribution graph for the training data

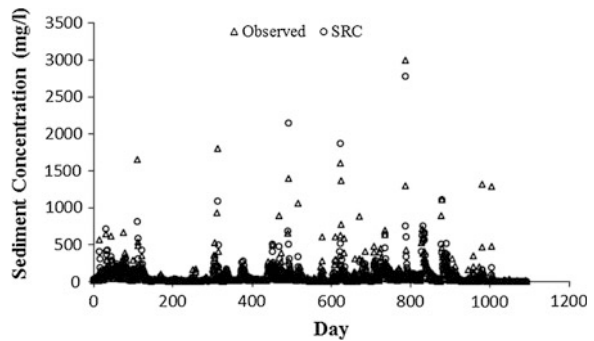
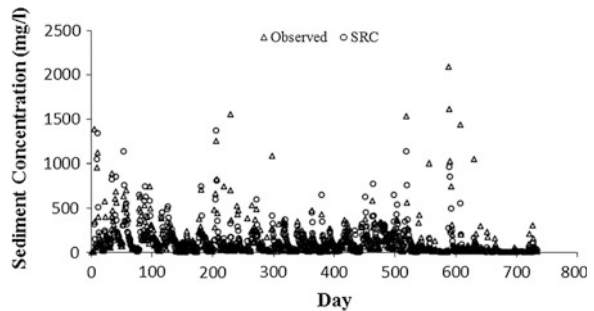


Fig. 7 Observed and SRC distribution graph for the testing data



3.2 MLR Model Results

For multiple linear regression (MLR), 5-years data are evaluated and the results are offered in figures. Distribution and scatter plots are shown for training data in Figs. 8 and 9 and for testing data in Figs. 10 and 11.

The correlation coefficient was obtained as $R = 0.862$ from Fig. 9. Although daily real-time suspended sediment concentration values are better than SRC values, the estimated results are worse than the observed actual values. In distribution

Fig. 8 Observed and MLR distribution graph for the training data

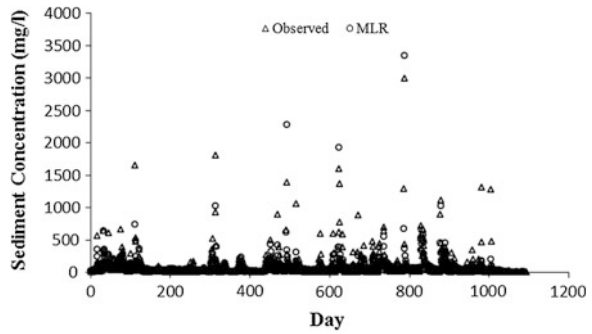


Fig. 9 Observed and MLR scatter graph for the training data

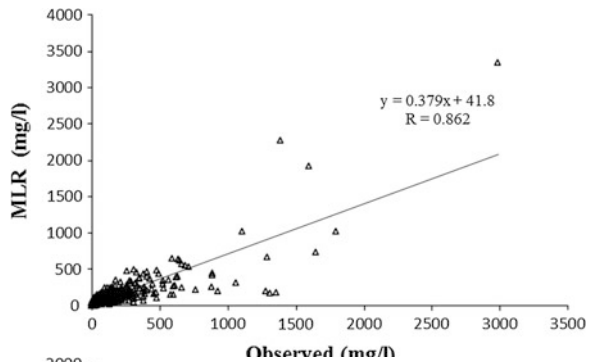


Fig. 10 Observed and MLR scatter graph for the testing data

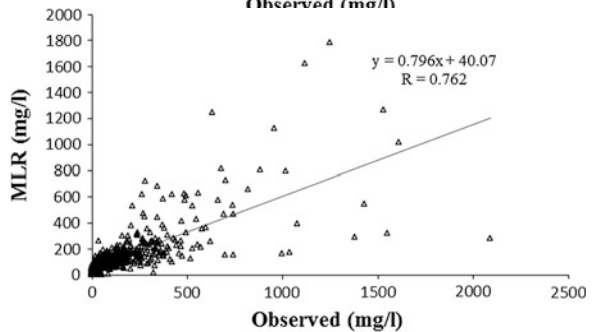


Fig. 11 Observed and ANN distribution graph for the testing data

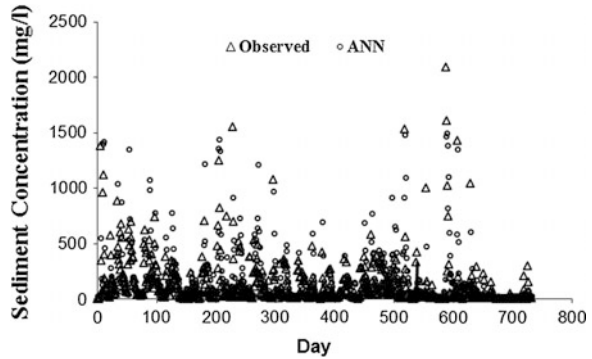
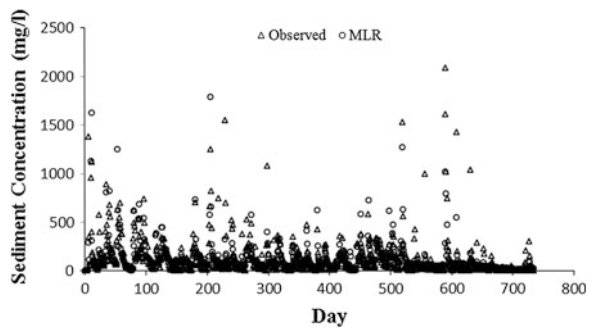


Fig. 12 Observed and MLR distribution graph for the testing data



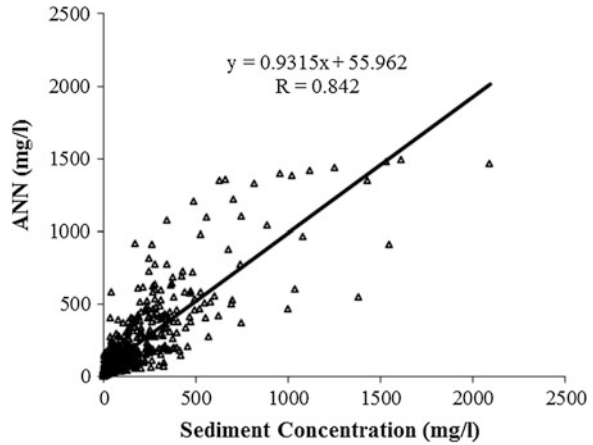
and scatter charts, MLR values are smaller than the actual values. The following figures are shown in Figs. 10 and 12 for testing data distribution and scatter plots.

The correlation coefficient were obtained as $R = 0.762$ from the generated graphic. Although daily real-time sediment concentration values is better results than the SRC values, the worst estimated results are observed according to the actual values. In distribution and scatter charts, MLR values are smaller than the actual values. It is observed from figures that MLR estimated test data perform better than the estimated training data.

3.3 Artificial Neural Network (ANN) Model Results

Five-year data were evaluated for ANN model and results are defined as follows. Training and testing data are separated into two parts as three inputs and one output and then entered into Matlab program. The results that created according to the rules are entered. Linguistic relationships between the temperature and flow and suspended sediment concentration rules are created and results are obtained.

Fig. 13 Observed and ANN scatter graph for the testing data



ANN models are evaluated for 5-year data created in Matlab program. Estimated testing results are shown in Figs. 11 and 13 as respectively the distribution and scatter plots.

The correlation coefficient was obtained as $R = 0.842$. The ANN estimated values are observed in the test phase and give better results than the SRC and MLR values. As can be seen from figures, the fit line of the ANN is closer to the exact line with a higher R-value than those of the SRC and MLR models. As seen from the scatter plots, the ANN model estimates are less scattered in comparison to the other models.

3.4 General Evaluation

Using daily real-time stream flow, suspended sediment concentration and mean water temperature data from Little Coal River, Danville station, correlation coefficient (R), the lowest mean squared error (MSE), the total squared error (MAE) are calculated for performance evaluation of SRC, MLR, ANN models. Results are used to compare the performance of model prediction and the observation data. Comparing parameters of MSE, MAE and R obtained from testing data are shown in Table 2.

When Table 2 is considered, ANN model gives better results than SRC and MLR models in all performance values.

Table 2 Comparing performances of models created for the Little Coal River, Danville station

Method	MSE ($m^3 s^{-1}$)	MAE ($m^3 s^{-1}$)	R
SRC	4,897.28	45.38	0.785
MLR	4,190.39	45.55	0.762
ANN	3,425.17	34.18	0.842

MSE Mean squared error, MAE Mean absolute error, R Correlation coefficient

4 Conclusions

In this study, sediment rating curve (SRC), multiple linear regression (MLR), and artificial neural network (ANN) models were investigated in order to improve methods to estimate the suspended sediment concentration. The mean water temperature, daily real-time flow rate, sediment concentration of 5 year data in the Little Coal River, Danville station, West Virginia were analyzed. Model comparisons were made using the research to see which model gave better results. Based on the comparison results, the ANN technique was found to perform better than the other models.

The accuracy of the ANN model in total sediment load estimation was also investigated and results were compared with those of the SRC and MLR models. Comparisons revealed that the ANN model had the best accuracy in total sediment load estimation.

For 5 year data, according to the MSE, MAE and R criteria, the best results were obtained in ANN model. In general, the worst results were obtained in MLR models.

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