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Modeling of streamflow- suspended sediment load relationship by adaptive neuro-fuzzy and artificial neural network approaches (Case study: Dalaki River, Iran)

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Abstract

Modeling of stream flow–suspended sediment relationship is one of the most studied topics in hydrology due to its essential application to water resources management. Recently, artificial intelligence has gained much popularity owing to its application in calibrating the nonlinear relationships inherent in the stream flow–suspended sediment relationship. This study made us of adaptive neuro-fuzzy inference system (ANFIS) techniques and three artificial neural network approaches, namely, the Feed-forward back-propagation (FFBP), radial basis function-based neural networks (RBF), geomorphology-based artificial neural network (GANN) to predict the streamflow suspended sediment relationship. To illustrate their applicability and efficiency,, the daily streamflow and suspended sediment data of Dalaki River station in south of Iran were used as a case study. The obtained results were compared with the sediment rating curve (SRC) and regression model (RM). Statistic measures (RMSE, MAE, and R^2) were used to evaluate the performance of the models. From the results, adaptive neuro-fuzzy (ANFIS) approach combined capabilities of both Artificial Neural Networks and Fuzzy Logic and then reflected more accurate predictions of the system. The results showed that accuracy of estimations provided by ANFIS was higher than ANN approaches, regression model and sediment rating curve. Additionally, relating selected geomorphologic parameters as the inputs of the ANN with rainfall depth and peak runoff rate enhanced the accuracy of runoff rate, while sediment loss predictions from the watershed and GANN model performed better than the other ANN approaches together witj regression equations in Modeling of stream flow–suspended sediment relationship.

Keywords**:** Adaptive neuro-fuzzy inference system; Artificial neural networks; Dalaki river; geomorphology; suspended sediment

1. Introduction

In trying to determining the active volume of reservoirs which can be for multiple purposes such as flood control, water supply, energy production, irrigation etc., it is also of necessity to accurately predict the quantity of sediments. The errors in predictions may result in reservoirs being filled with sediments before it the completion of its useful life. In the basin and river investigations, establishing a relationship between discharge and sediment load has always been one of the most important research subjects and of much focus by numerous researchers. The temporary and spatial change in the hydrologic conditions and basin characteristics together with the difficulties in determining their effects have necessitated the adoption of the black box models in suspended sediment estimations. Models established to predict the sediment load from river discharge should not depend on assumptions because such assumed predictions would not be objective and

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may result in inaccurate consequences. Moreover, these may cause increasing cost of water resources' planning and operations or decrease in the expected economic lifetime.

There has been little or no success yet in modelling the complete process of sediment load transport in rivers using the classical approach of hydromechanics reason being that particle movements in turbulent flow as well as the properties of the particles are all random (Trung Tuan *et al*., 2003). A linear relationship among variables is assumed in many of the available techniques for time series analysis. In the real world, however, temporal variations in data do not exhibit simple regularities and are difficult to analyze and predict accurately. Generally, black box models are divided into: linear and non-linear and in particular, artificial neural networks (ANN) method is commonly used in the modeling of non-linear system behavior. Capability of ANNs to establish nonlinear links between inputs and outputs makes them useful tools for modeling hydraulic and hydrological phenomena (ASCE, 2000). ANN models have been successfully applied to many tasks in environment and hydrology engineering (Sahoo *et al*., 2006; Kim *et al*., 2008; Tsai *et al*., 2009; Nourani et al., 2008, 2009). ANN's employment in suspended sediment estimation and prediction has recently been determined (Jain, 2001; Agarwal *et al*., 2005; Cigizoglu and Alp, 2006).

Zhu *et al*. (2007) proposed an ANN model for simulating the monthly suspended sediment flux in the Longchuanjiang River in China. According to the proposed model, suspended sediment flux had a relationship with the average rainfall, temperature, rainfall intensity and flow discharge. The results illustrated the ANN model of being capable of simulating monthly suspended sediment flux with fairly good accuracy concerning proper variables and their correlation to the previous month (lagging effect) on the suspended sediment flux. In spite of suitable flexibility of ANN in modeling hydrologic time series, sometimes there is a shortage when signal fluctuations are highly non-stationary and physical hydrologic process operates under a large range of scales varying from 1 day to several decades. In such an uncertain situation, the Fuzzy Inference System (FIS) may be employed in the estimation of uncertainties in the real situations. The hybrid of ANN and FIS is one of the research area of focus. This hybrid makes use of the combined of both the ANN and FIS, namely the Neuro-Fuzzy (NF) systems. The adaptive neuro-fuzzy inference system (ANFIS) is a hybrid scheme that utilizes the learning capability of the artificial neural network or ANN to derive the fuzzy if-then rules with appropriate membership functions worked out from the training pairs, which in turn leads to the inference (Jang and Sun, 1995; Tay and Zhang, 1999). The difference between the common neural network and the ANFIS is that, while the former captures the underlying dependency in the form of the trained connection weights, the latter does so by establishing the fuzzy language rules (Azamathulla *et al*., 2008). The treatment of data non-linearities using this methodhas been recently found to be useful in fields like hydrology (Nayak *et al*., 2004; Kisi, 2005), fluvial hydraulics (Bateni et al., 2007), river flow modeling (Zounemat-Kermani and Teshnehlab, 2008) and estimation of scour depth near pile groups (Zounemat-Kermani *et al*., 2009).

There exist various studies on the application of fuzzy logic and neurofuzzy algorithms in prediction of sediment. For example, Tayfur *et al*. (2003) proposed a fuzzy logic algorithm using the rainfall intensity and slope data to estimate sediment loads from bare soil surfaces and revealed a better performance of the fuzzy model under very high rainfall intensities, over different slopes, over very steep slopes and under different rainfall intensities. Kisi *et al*. (2006) developed a fuzzy logic approach to estimate SSC in rivers. The study was based on stream flow and SSC data of Quebrada Blanca Station operated by the United States Geological Survey. The results of the study revealed a possible successful application of the fuzzy model for SSC prediction. Lohani *et al*. (2007) used a fuzzy logic approach to model the stage–discharge–SSC relationship. The model has been applied in two gauging sites in the Narmada basin in India. The results revealed the ability of the fuzzy model to produce much better results than SRC method. Kisi *et al*. (2008) studied the accuracy of an adaptive neuro-fuzzy computing technique in monthly suspended sediment prediction in Kuylus and Salur Koprusu stations in Kizilirmak Basin in Turkey. The results illustrated that NF algorithm provided better performance than ANN and SRC models. Rajaee *et al*. (2009) studied the advantages of both ANN and neuro-fuzzy computing techniques in daily suspended concentration simulation in two hydrometry gauging stations (Little Black River Station and Salt River Station) in the United

States. The obtained results illustrated that ANN and NF models are consistent with the observed SSC values; while they depict better results than MLR and SRC methods.

The present study summarizes the recent results obtained based on the performances of an adaptive NF computing technique in daily suspended sediment prediction using the daily rainfall, streamflow and suspended sediment concentration data from Dalaki River Catchment near Persian Gulf in Iran. The estimation accuracy of ANFIS model is compared with three different artificial neural networks (ANN) techniques, namely, the Feed-forward back-propagation (FFBP), radial basis function-based neural networks (RBF), geomorphology-based artificial neural network (GANN). A comparison of the simulation from ANN and ANFIS was made with the conventional multi-linear regression (MLR) and conventional sediment rating curve (SRC) in terms of the selected performance criteria which was found in the testing of the ANN and ANFIS simulations. This study is concerned with the application of neuro-fuzzy and neural networks which are more powerful tools for modelling suspended sediment.

The methodology of constructing the ANFIS model and three different artificial neural networks (ANN) techniques for daily suspended sediment concentration simulation and conventional multi-linear regression (MLR) and sediment rating curve (SRC) have also been presented. The theorem, networks structures, and parameters estimating algorithms have been described. While a presentation of the study watershed, available data, and models constructions have also been given. Subsequent sections also presented the application of SRC, MLR, FFBP, RBF, GANN and ANFIS models on daily suspended sediment data, with the results clearly stated and discussed.

2. Methodology

2.1. Sediment Rating Curve (SRC)

The establishment of a SRC is of great importance in hydrology. The costly and time consuming nature of the sediment has warranted the daily measurement of its discharge. The SRC is used to assess the sediment discharge corresponding to the measured flow discharge.

Sediment rating curve expresses the sediment load, C, at a cross-section from the river through its discharge, Q, as given by the formula:

$$C = aQ^b \tag{1}$$

where a and b are the coefficients that provide the best relationship between discharge and the sediment load. These parameters are generally obtained by least squares method. For a given set of *C* and *Q* data, only one solution point (*a* and *b*) values are obtained. In this case, *a* and *b* coefficients are accepted as constant through all process. Initial and environmental conditions are very important in the formation of sediment quantity.

2.2. Multi-linear regression model

Sediment yield is the net result of erosion and deposition processes and is thus dependent on all variables that control erosion and sediment delivery. Soil erosion is dependent on local topography, soil, climate and vegetation whereas sediment delivery is influenced by catchment morphology, land use and drainage network form and density (Restrepo *et al*., 2006; Vanacker *et al*,, 2009).

The inability of one single catchment property alone to explain a large part of the observed variation in sediment yield, often, the construction of multi-linear regression is necessary (Altun *et al*., 2007; Cigizoglu, 2006; Sinnakaudan *et al*., 2006).

2.3. The structure of the ANNs

2.3.1. Feed-forward back-propagation algorithm (FFBP)

Given a training set of input-output data, the most common learning rule for multi-layer perception is the back-propagation algorithm (BPA). This involves two phases: a feed-forward phase in which the external input information at the input nodes is propagated forward to compute the output information signal at the output unit, and a backward phase in which modifications to the connection strengths are made based on the differences between the computed and observed information signals at the output units (Eberhart and Dobbins, 1990). The neural network structure in this study possessed a three-layer learning network which consists of an input layer, a hidden layer and an output layer. The present study utilized the Levenberge Marquardt optimization technique. This technique is more powerful than the conventional gradient descent techniques (Hagan and Menhaj, 1994; El-Bakyr, 2003; Cigizoglu and Kisi, 2005a). While back propagation with gradient descent technique is a steepest descent algorithm, the Marquardte Levenberg algorithm is an approximation to Newton's method. Hagan and Menhaj (1994) demonstrated the Marquardt algorithm as being very efficient when training networks with up to a few hundred weights. Although the Marquardt algorithm computational requirements are much higher for each iteration, the increased efficiency outweighs this limitation. This is especially true when high precision is required. It was also found that in many cases, the Marquardt algorithm converged when other back-propagation techniques failed to converge (Hagan and Menhaj, 1994).

2.3.2. The radial basis function-based neural networks (RBF)

RBF networks were introduced into the neural network literature by Broomhead and Lowe (1988). The RBF network model is motivated by the locally tuned response observed in biological neurons. Neurons with a locally tuned response characteristic can be found in several parts of the nervous system, for example, cells in the visual cortex sensitive to bars oriented in a certain direction or other visual features within a small region of the visual field (Poggio and Girosi, 1990). These locally tuned neurons show response characteristics bounded to a small range of the input space. The theoretical basis of the RBF approach lies in the field of interpolation of multivariate functions. The solution of the exact interpolating RBF mapping was made to pass through through every data point (xs, ys). In the presence of noise, the exact solution of the interpolation problem is typically a function oscillating between the given data points. An additional problem with the exact interpolation procedure is that the number of basis functions is equal to the number of data points thereby making the calculation of the inverse of the N _ N matrix f intractable in practice. The interpretation of the RBF method as an artificial neural network consists of three layers: a layer of input neurons feeding the feature vectors into the network; a hidden layer of RBF neurons, calculating the outcome of the basis functions; and a layer of output neurons, calculating a linear combination of the basis functions (Taurino *et al*., 2003). The different numbers of hidden layer neurons and spread constant were tried in the study.

2.3.3. Geomorphology-based artificial neural network (GANN)

In this study Artificial Neural Network (ANN) was developed using watershed-scale geomorphologic parameters. Such a geomorphology-based artificial neural network (GANN) is utilized to estimate sediment losses of Dalaki watershed.

Majority of the authors are of the opinion that the geomorphologic characteristics of the watershed have strong influences on the stream flow-suspended sediment relationship. This issue is reflected both in physically based as well as geomorphology-based models. While including geomorphologic information in models appears to be a laudable goal, several researches (Sarangi, 2005; Raghuwanshi, 2006) believe that the natural heterogeneity and the multitude of processes that occur over the watershed scale tend to average out geomorphologic effects, and the hydrologic response can therefore be represented by simple methods. There exist a number of similarities between the geometric nature of a channel network and an ANN, and this suggest that the geomorphologic properties of a river network may be represented in an explicit fashion in the architecture of an ANN.

Geomorphologic parameters describing the land surface drainage characteristics and surface water flow behavior were empirically associated with measured rainfall and runoff data and used as input to a three-layered back-propagation feed-forward neural network model. In this study Morphological parameters such as bifurcation ratio, area ratio, channel length ratio, drainage factor and relief ratio were selected as inputs to the ANN model.

2.4. The adaptive neuro-fuzzy inference system (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS), first introduced by Jang (1993), is a universal approximation which is capable of approximating any real continuous function on a compact set to any degree of accuracy (Jang *et al*., 1997).

The ANFIS is a multilayer feed forward network which uses neural network learning algorithms and fuzzy reasoning to map an input space to an output space. With the ability to combine the verbal power of a fuzzy system with the numeric power of a neural system adaptive network, ANFIS has been shown to be powerful in modeling numerous processes, such as motor fault detection and diagnosis, power systems dynamic load, wind speed, forecasting system for the demand of teacher human resources, and real time reservoir operation.

ANFIS serves as a good platform for learning, constructing, expensing, and classifying. It has the advantage of permitting the extraction of fuzzy rules from numerical data or expert knowledge and adaptively constructs a rule base. Furthermore, it can tune the complicated conversion of human intelligence to fuzzy systems. However, its main disadvantage is the time required for training structure and determining parameters, which was rather too lengthy. For simplicity, the fuzzy inference system under consideration was assumed to have two inputs, x and y, and one output, z. For a first-order Sugeno fuzzy model [35], a typical rule set with two fuzzy if–then rules can be expressed as:

Rule 1: If x *is* A_1 *and* y *is* B_1, *then* $f_1 = p_1x + q_1y + r_1$

Rule 2: If x *is* A_2 *and* y *is* B_2, *then* $f_2 = p_1x + q_2y + r_2$ (2)

where pi, qi and ri (i= 1 or 2) are linear parameters in the then-part (consequent part) of the first-order Sugeno fuzzy model. Figure 1 describes the resulting Sugeno fuzzy reasoning system. The architecture of ANFIS consists of five layers (Fig. 1), and a brief introduction of the model is as follows.

Layer 1: Input nodes. Each node of this layer generates membership grades which belong to each of the corresponding appropriate fuzzy sets, using membership functions.

$$O_{1,i} = \mu_{Ai}(x) \quad \text{for } i = 1, 2$$
$$O_{1,i} = \mu_{Bi-2}(y) \quad \text{for } i = 3, 4 \tag{3}$$

where x, y are the crisp inputs to node i, and A_i, B_i (small, large, etc.) are the linguistic labels characterized by appropriate membership functions μ_{Ai}, μ_{Bi}, respectively. Due to smoothness and concise notation, the Gaussian and bell-shaped membership functions are increasingly popular for specifying fuzzy sets. The bell-shaped membership functions have one more parameter than the Gaussian membership functions, so a nonfuzzy set can be approached when the free parameter is tuned. The bell-shaped membership function is used in this study.

$$\mu_{A_i} = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}} \quad \mu_{B_{i-2}} = \frac{1}{1 + \left|\frac{y-c_i}{a_i}\right|^{2b_i}} \tag{4}$$

where $\{a_i, b_i, c_i\}$ is the parameter set of the membership functions in the premise part of fuzzy if–then rules that changes the shapes of the membership function. Parameters in this layer are referred to as the premise parameters.

Layer 2: Rule nodes. In the second layer, the AND operator is applied to obtain one output that represents the result of the antecedent for that rule, i.e., firing strength. Firing strength refers to the degrees to which the antecedent part of a fuzzy rule is satisfied and it shapes the output function for the rule. Hence, the outputs $O_{2,k}$ of this layer are the products of the corresponding degrees from Layer 1

$$O_{2,k} = w_k = \mu_{Ai}(x) \times \mu_{Bi}(y) \qquad k = 1, \ldots, 4;$$
$$i = 1, 2; \quad j = 1, 2 \tag{5}$$

Layer 3: Average nodes. In the third layer, the main objective is to calculate the ratio of each ith rule's firing strength to the sum of all rules firing strength. Consequently, wi is taken as the normalized firing strength

$$O_{3,i} = \overline{w_i} = \frac{w_i}{\sum_{k=1}^{4} w_k} \quad i = 1, \ldots, 4 \tag{6}$$

Layer 4: Consequent nodes. The node function of the fourth layer computes the contribution of each ith rules toward the total output and the function defined as

$$O_{4,i} = \overline{w_i} f_i = \overline{w_i}(p_i x + q_i y + r_i), \quad i = 1, \ldots, 4 \tag{7}$$

where wi is the ith node's output from the previous layer. Parameters {pi, qi, ri} are the coefficients of this linear combination and are also the parameter set in the consequent part of the Sugeno fuzzy model.

Layer 5: Output nodes. The single node computes the overall output by summing all the incoming signals. Accordingly, the defuzzification process transforms each rules' fuzzy results into a crisp output in this layer

$$O_{5,1} = \sum_{i=1}^{4} \overline{w_i} f_i = \frac{\sum_{i=1}^{4} w_i f_i}{\sum_{i=1}^{4} w_i} \tag{8}$$

This network is trained based on supervised learning. Therefore, the main target here is to train adaptive networks such that it can approximate unknown functions given by training data and then find the precise value of the aforementioned parameters. The distinguishing characteristic of the approach is that ANFIS applies a hybrid-learning algorithm, the gradient descent method and the least-squares method, to update parameters. The gradient descent method is employed to tune premise non-linear parameters ({ai, bi, ci}), while the least-squares method is used to identify consequent linear parameters ({pi, qi, ri}). As shown in Figure 1, the circular nodes are fixed (i.e., not adaptive), without parameter variables, and the square nodes have parameter variables (the parameters are changed during training). The learning procedure task has two steps: Step one involves the identification of the consequent parameters using the least square method with the assumption that the antecedent parameters (membership functions) are fixed for the current cycle through the training set, while propagating the error signals backward. Premise parameters are updated through minimizing the overall quadratic cost function using the gradient descent method, while the consequent parameters remained fixed. The detailed algorithm and mathematical background of the hybrid-learning algorithm can be found in [21].

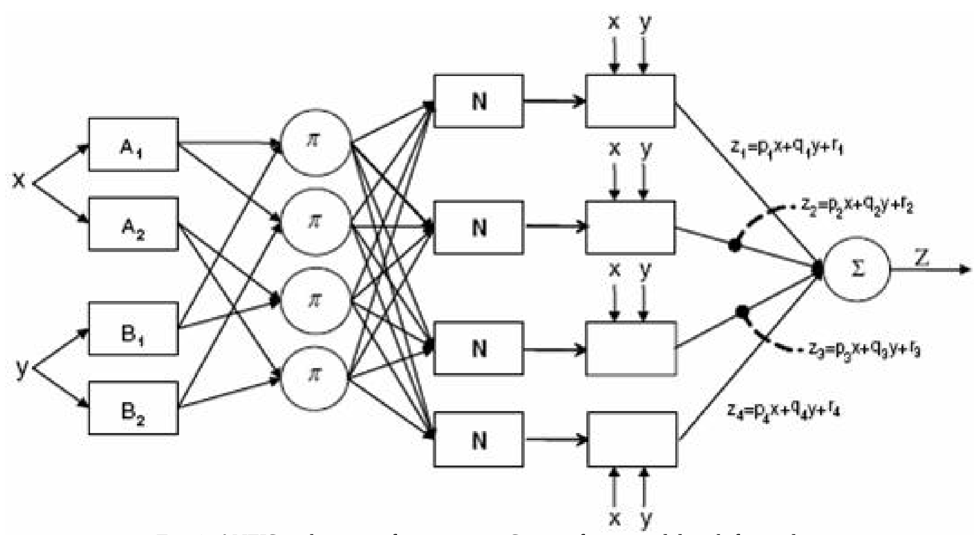

Fig. 1. ANFIS architecture for two-input Sugeno fuzzy model with four rules

3. Description of study area and data

Dalaki River Basin, located in southern Iran was selected for the study, with Dalaki as the main river in the water shed. It has a catchment area of 158.35 km^2 and lies between 27° 07′ 52″ and 30° 01′ 02″N latitude and 50° 01′ 06″ and 52° 45′ 06″E longitudes (Fig. 1). The area consists of hills and alluvial plains, with sedimentary geology including Gori limestone, Aghajari marl, Bakhtiyari conglomerate and Quaternary alluvium based on a 1:100,000 available geological mapping. It has a slope range from 5.2 to 15.2%, with an average watershed of 8.2 %. The elevation of the watershed ranges from 50 m to 90 m above mean sea level. The daily mean temperature ranges from a maximum of 43°C to a minimum of 3°C, and the mean annual temperature is 18.5°C.

An arid climate dominates this area, with an annual average rainfall of 150 mm and relative air humidity of 52%. Generally, it is characterized with about 80% of precipitation falls in 2-3 intense storm events, with is normally predominant towards the end of autumn and winter, with a high temporal and spatial variability typical of such arid regions. All streams are seasonal and require 8 mm/min of rainfall intensity to generate runoff. Table 1 represents the statistical parameters of streamflow and sediment concentration data of Dalaki station.

Land uses comprised Rangeland, uncultivated lands without vegetation cover, desert pavement, urban area and cropland. The dominant native plants are *Seidlitzia florida*, *Artemisia sieberi*, *Salsola sp*, *Alhagi camelorum* and *Halocnemum strobilaceum*. The main soil types are Lithic

Torriortants and Gypsic Haplocalcids and Typic Haplosalids in terms of U.S.Taxonomy (2002).

In this study a 10 year (1998-2008) data set including daily discharge, sediment discharge or concentration of Dalaki gauging station was used for model calibration.

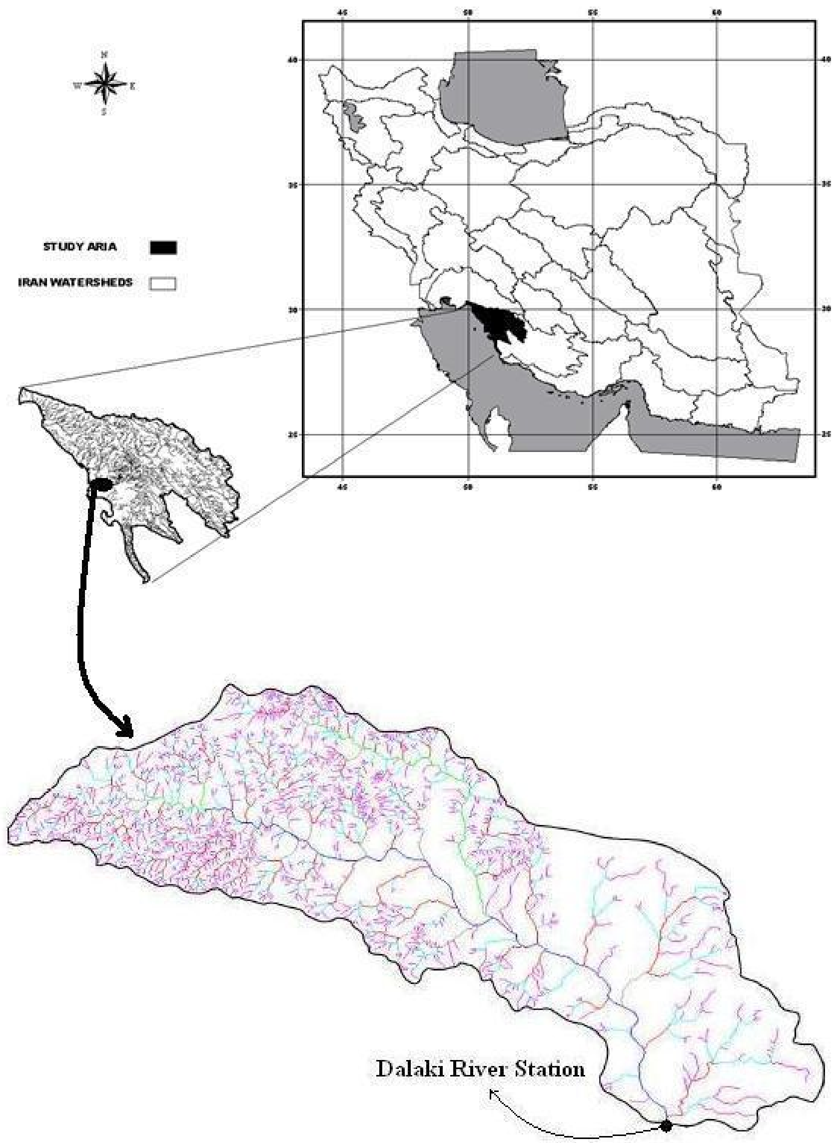

Fig. 1. Location of the Dalaki River Station

Table 1. The daily statistical parameters of data set for the station

Station	Basin area (km^2)	Data type	X_{mean}	S_x	C_v	C_{sx}	X_{max}	X_{min}
Dalaki river station	158.35 km^2	Flow (m^3s^{-1})	0.85	2.3	2.7	10.5	85	0.5
		Sediment ($mg1^{-1}$)	52	98	1.88	9.85	5200	50

S_x: standard deviation; C_v (S_x/ X_{mean}): coefficient of variation; C_{sx}: coefficient of skewness.

In Dalaki River gauging Station, the data from January 1, 2002 to June 1, 2007 and from June 2, 2007 to June 8, 2008 were used for training and testing sets, respectively. Figure 2 shows the time series of data related to daily discharge and suspended sediment load.

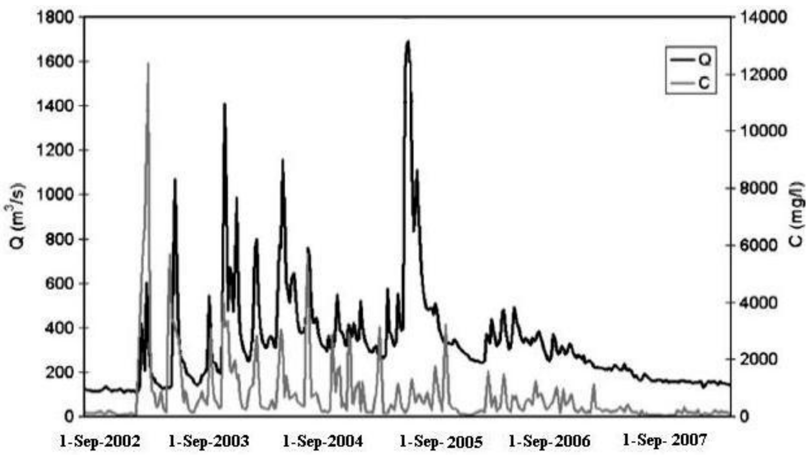

Fig. 2. River discharge and suspended sediment load time series (6 years) for Dalaki River Station

4. Data preparation and standardization

Out of the 101 data sets available for the runoff rate and sediment yield in 5 years, about 60% were used for ANN model development while the remaining 40% (≈40 sets) were used for model validation. Of the data used for model development, 60% (≈30 sets) were used for training while 40% (≈20 sets) were used for model testing. The Neural Works Professional II + version 5.23 and Neural Network toolbox of MATLAB 6.5 tools were used in developing the ANN models.

5. Estimation of geomorphologic parameters

The present study utilized selected geomorphologic parameters of the watershed (Table 1) in developing development the GANN models. An estimation of geomorphologic parameters of the study area was made using a map scale of 1:100000 and Strahler ´s ordering system (Schuller, 1999). The value of R_A, R_B, and R_L lie in the ranges usually found in natural watersheds.

Table 2. Geomorphologic parameters estimated for Dalaki River Basin

Geomorphologic parameter	Dalaki Basin				
Perimeter (km)	138.2				
Area (km^2)	156.6				
Maximum length (km)	42.3				
Maximum elevation (m)	90				
Minimum elevation (m)	50				
Watershed relief (km)	0.05				
Relief ratio	0.008				
Relative relief	0.005				
Elongation ratio	0.745				
Mean slope (%)	8.2 %				
Stream characteristics (Strahler's stream ordering system)	Number of streams	Length (km)	Area (km^2)	Mean length (km)	Mean area (km^2)
1st order streams	52	19.56	45.8	0.78	0.564
2nd order streams	23	36.24	65.6	1.78	1.634
3rd order streams	6	10.12	18.4	2.56	6.354
4th order streams	2	4.68	8.4	2.92	18.54
Horton's parameters		R_L=2.765	R_B=4.655	R_A=5.263	
Total length of streams of all orders (km)	85.5				
Stream frequency of the watershed (km^{-2})	3.445				
Drainage factor of the watershed	0.80				
Basin Shape factor	1.658				
Form factor	0.405				
Circulatory ratio	0.652				
Drainage density (km^{-1})	1.652				
Ruggedness number	0.065				
Hypsometric integral (H_{si})	0.46				

6. Models application

6.1. Sediment Rating Curve (SRC)

Different methodologies have been applied to daily data to derive sediment rating curves at Dalaki River gauge. The regression coefficients *a* and *b* were calculated by a least squares regression on the logarithms of discharge and suspended sediment concentration. Two rating relationships were developed using data set grouped according to seasons. The two regression lines were almost parallel. For a given discharge, the value of concentration in summer was lower than in winter. This concentration variation arose from the presence of vegetation cover during the summer season which protected the soil from erosion (Fig. 3).

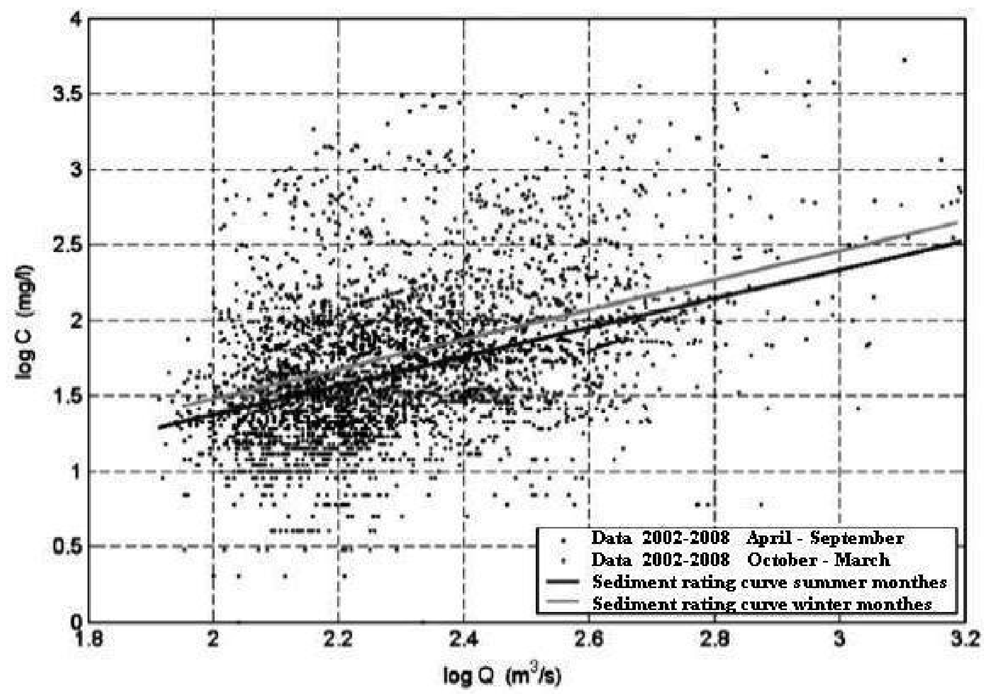

Fig. 3. Sediment rating curves for Dalaki River gauge

6.2. Multi Linear Regression

A comparison of other models with the developed model was made using the regression model (Eq. 3), Tahmoures, 2008). In this research, various morphological catchment properties, land use and soil texture were analyzed to explain the large variability in sediment yield. In most cases, a stepwise linear regression technique was applied. The following models explained most of the variation in observed sediment yield, having the multi-co linearity between independent variables kept to an acceptable minimum:

$$\ln SSY\ (t\ ha^{-1}\ year^{-1}) = 4.25 - 0.66 \ln A - 0.81 \ln HI + 0.11 \ln Df$$

$$SY\ (g/l) = 0.32\ Rr + 18.6\ HI + 10.6\ Sf - 325\ Df \qquad (9)$$

where SSY= specific sediment yield (t ha^{-1} $year^{-1}$); A= catchment area (ha); HI= hypsometric integral; Df= Drainage factor; SY= sediment yield (g/l); Rr = Relief ratio; Sf= Basin Shape factor. The model which predicts SSY explains 82% of the observed variability, whereas catchment area alone already explains 66%. For SY, catchment area is not part of the model, which explains 92% of the observed variation.

6.3. Application of ANNs to data

The four dimensionless geomorphological parameters used in Eq. (3) (Table 1) were mathematically associated with the observed runoff rate as R which were inputted to the ANN model in order to develop the GANN.In this study, two algorithms written in MATLAB for feed-forward back-propagation (FFBP) and radial basis functions (RBF) were employed for ANN simulations. The ANN network structure consisted of three layers, i.e. input layer, single hidden layer and output layer. The input layer was prepared using different combinations of hydrometeorological data. The application of the ANNs to time series data consisted of two steps. The first step was the training of the neural networks. This included daily rainfall and flow data describing the input and sediment load data describing the output to the network in order to obtain the inter-connection weights. Once the training stage was completed, the ANNs were applied to the testing data. As given in Table 3, approximately 5 years of data were used to train the networks and less than one year was used to test it. The training set comprised the first 2500 values while the testing set covered the last 550 values. It is evident that there are variation between the statistics of training and testing data sets. Other configurations have also been considered for training and testing sets. First, 550 values were considered for testing and the following 2,500 values constituted the training set. However, the statistics for both sets in this scenario differed from each other. Other options such as taking the testing data set from the middle part of the whole series did not make much meaning from the point of hydrology, since the first part and the last part of the whole series constituted the training data set, which accounted for its discontinuity. Determining an appropriate architecture of a neural network for a particular problem is an important issue since the network topology directly affects its computational complexity and its generalization capability. For FFBP, the number of hidden layers and the number of the nodes in the input and hidden layers were determined after trying various network structures. There are several methods to avoid overfitting in ANNs. These methods are summarized by Giustolisi and Laucelli (2005). In the present study, ‘‘Early stopping’’ technique was adopted. This technique involved the splitting of the training set into two subsets: the estimation and the validation. In this study, the first 2000 values in the training set were considered for estimation and the last 500 for validation. The mean square error (MSE) was computed at each training step by means of the validation subset, while the search direction was computed by means of estimation subset. The training stopped as soon as the validation error rate increased. This method was also used in determining the iteration. Accordingly, for FFBP training experiments, the iteration number was found as 150. Initially, weight values were assigned normally distributed numbers in the interval (-3, +3). A tangent sigmoid function was used as a transfer function. Learning and momentum rate parameters are adaptive, i.e. they change during the training stage dynamically. In the presented study, adaptive (variable) learning rate was used throughout the simulations. The learning rate values varied from 0 to 1. The performance of the algorithm is very sensitive to the proper setting of the learning rate. A relatively high learning rate results in oscillation and instability of the algorithm, similarly, a relatively low learning rate results in an increase in the time for convergence of the algorithm. It is not practical to determine the optimal setting for the learning rate before training, and, in fact, the optimal learning rate changes during the training process, as the algorithm moves across the performance surface. An adaptive learning rate will attempt to keep the learning step size as large as possible while keeping the learning stable. The learning rate is made responsive to the complexity of the local error surface. First, the initial network output and error are calculated. At each epoch, new weights and biases are calculated using the current learning rate, followed by the calculation of new outputs and errors. If the new error exceeds the old error by more than a predefined ratio, the new weights and biases are discarded (by multiplying with 0.7). In addition, the learning rate is decreased. Otherwise, the new weights, etc., are retained. If the new error is less than the old error, the learning rate is increased (by multiplying with 1.05). This procedure increases the learning rate, but only to the extent that the network can learn without large error increament. Thus, a near-optimal learning rate is obtained for the local terrain. A resultant stable learning from an large learning rate consequently increased the rate of learning. However, a more than proportional increase in learning rate, which cannot guarantee a decrease in error, results in a corresponding decrease in learning until it attains stability.

Table 3. Training and testing periods for different ANN applications

	Study type		
	Simulation I	Simulation II	Simulation III
Training	01.01.2002-01.06.2007	01.01.2002-01.06.2007	01.01.2002-01.06.2007
Testing	02.06.2007-08.06.2008	02.06.2007-08.06.2008	02.06.2007-08.06.2008

Hidden layer unit number was found separately for each of the input layer scenarios. In order to circumvent the local minima problem faced in FFBP simulations, many repetitions of the same FFBP configuration have been made. Accordingly, the FFBP repetition number was found as 20 for Simulation I, 18 for Simulation II and 25 for Simulation III studies. The experiment with the lowest MSE in testing set was considered as the representative FFBP simulation. The examination of the cross-correlations between different hydrometeorological series provided preliminary information regarding the number of the nodes in the input layer. It was shown that a detailed preliminary statistical analysis of the data sheds light to the structure of the ANN input layer (Sudheer *et al*., 2002; Cigizoglu, 2005a). For RBF, the same input layer structure with FFBP was employed. Several iteration numbers varying from 5 to 100 were tested. The iteration number equals to 35 provided best performance criteria. Various spread values between 0 and 1 were considered for RBF simulations. The spreads providing best performance criteria for each RBF configuration are given in Table 5. The input and output data were scaled between 0.1 and 0.9 to overcome problems associated with upper-limit and lower-limit saturation. The performance evaluation measures were the mean square error (MSE) and the coefficient of determination (R^2) between simulated and observed sediment loads. However, in the selection of the most appropriate ANN configuration, MSE had the priority in the decision making. But in general, the R^2 values were in harmony with MSE values. An additional evaluation criterion, total sediment load of the whole testing period, was also considered. This comparison in accumulated sediment load plays an important role in reservoir management (especially when considering an annual load). The simulation experiments were carried out in three steps: the first step involved simulating suspended sediment load data using rainfall measurements as input; followed by simulating suspended sediment load data using only flow data as input; and finally simulating suspended sediment load data using both rainfall and flow data as input. Conventional multi-linear regression was also applied to the same data for the purpose of comparison.

Table 4. The cross-correlations between two different hydrometeorological series

	Rainfall (mm)-sediment (tons/day)	Flow (m3/s)-sediment (tons/day)	Rainfall (mm)- flow (m3/s)
$r_{x,y,0}$	0.289	0.655	0.185
$r_{x,y,1}$	0.389	0.370	0.390
$r_{x,y,2}$	0.229	0.159	0.403
$r_{x,y,3}$	0.89	0.097	0.335

6.4. Suspended sediment load estimation using ANFIS technique

Adaptive NF model is applied as an effective approach in handling nonlinear and noisy data, especially in situations where the relationships among physical processes are not fully understood. It is also particularly well suited for modeling complex systems on real time basis. The aim of this research was to investigate the efficiency of ANN and ANFIS models for predicting suspended sediment load a day ahead. With respect to the statistical analysis presented in Table 6, the following combinations, including daily stream flow and rainfall of current and previous days, and suspended sediment concentration of previous days, are tried using ANFIS model to estimate current suspended sediment concentration. The input combinations used in this application to estimate suspended sediment concentrations for the Dalaki River station are (i) Q_t; (ii) Q_t, and Q_{t_1}; (iii) Q_t, Q_{t_1}, and Q_{t_2}; (iv) Q_t, Q_{t_1}, and S_{t_1}; (v) Q_t, Q_{t_1}, S_{t_1} and S_{t_2}; (vi) Q_t, Q_{t_1}, S_{t_1}, S_{t_2} and S_{t_3}; (vii) Q_t, Q_{t_1}, S_{t_1}, S_{t_2} and R_t and (viii) Q_t, Q_{t_1}, S_{t_1}, S_{t_2}, R_t and R_{t_1}, where Q_t, S_t and R_t represent the stream flow, sediment concentration and rainfall at day t, respectively.

Table 5. The performance criteria (MSE and coefficient of determination) values for ANNs obtained for the testing periods

ANN model inputs	FFBP			RBF			GANN		
	Nodes in hidden layer	MSE (tons^2/day^2)	R^2	S (spread parameter)	MSE (tons^2/day^2)	R^2	Nodes in hidden layer	MSE (tons^2/day^2)	R^2
R_t (Simulation I)	4	657 102	0.018	0.5	653 849	0.025	3	162 749	0.873
R_t, R_{t_1} (Simulation I)	3	631 230	0.098	0.7	627 231	0.095	6	151 863	0.864
R_t, R_{t_1}, R_{t_2} (Simulation I)	1	566 536	0.136	0.8	578 496	0.150	1	122 463	0.861
R_t, R_{t_1}, R_{t_2}, R_{t_3} (Simulation I)	3	520 490	0.213	0.7	562 128	0.174	3	123 672	0.871
Rt, R_{t_1}, R_{t_2}, R_{t_3}, R_{t_4} (Simulation I)	6	567 071	0.120	0.4	599 258	0.159	5	127 659	0.870
Q_t (Simulation II)	1	162 749	0.813	0.6	141 956	0.819	5	83 245	0.786
Q_t, Q_{t_1} (Simulation II)	3	151 863	0.827	0.5	136 739	0.836	5	111 619	0.873
Q_t, Q_{t_1}, Q_{t_2} (Simulation II)	5	122 463	0.873	0.3	115 439	0.878	3	162 749	0.864
Q_t, Q_{t_1}, Q_{t_2}, Q_{t_3} (Simulation II)	5	123 672	0.864	0.3	122 976	0.869	3	123 672	0.861
Q_t, Q_{t_1}, Q_{t_2}, Q_{t_3}, Q_{t_4} (Simulation II)	5	127 659	0.861	0.3	121 845	0.870	4	162 749	0.871
R_t, R_{t_1}, R_{t_2} and Q_t (Simulation III)	3	83 245	0.871	0.2	86 122	0.913	3	151 863	0.873
Rt, R_{t_1}, R_{t_2}, Q_t and Q_{t_1} (Simulation III)	3	111 619	0.870	0.3	92 189	0.905	3	122 463	0.864
R_t, R_{t_1}, R_{t_2}, Qt, Q_{t_1} and Q_{t_2} (Simulation III)	4	117 432	0.786	0.2	97 665	0.889	4	123 672	0.861
R_t, R_{t_1}, Q_t and Q_{t_1} (Simulation III)	3	65 984	0.897	0.3	59 485	0.921	5	127 659	0.871

Table 6. The statistical parameters of data set for the station

Data set	Data type	x_{mean}	S_x	C_v (S_x/x_{mean})	C_{sx}	x_{max}	x_{min}	x_{max} / x_{mean}
Training	Flow (m^3/s)	18.6	23.7	1.31	3.68	85	0.5	8.96
	Sediment (t)	1567	5430	4.77	10.43	85.77	3.5	65.8
Testing	Flow (m^3/s)	16.2	16.8	1.05	1.88	44	0.8	5.66
	Sediment (t)	1460	2431	2.84	5.33	32.66	14.65	11.48

The ANFIS models were tested and the results were compared by means of RMSE, MAE and R^2 statistics. The RMSE, MAE and R^2 statistics of each ANFIS model in test period are given in Table 7. The final architectures of the ANFIS models found after many trials are also provided in this table. Table 7 indicates the number of membership functions of each input variable. Two membership functions are found to be sufficient for the suspended sediment estimation. From Table 7, it is seen that the ANFIS model whose inputs are current stream flow and rainfall, one previous stream flow and two previous suspended sediment values has the lowest RMSE value (214 mg/l). However, the ANFIS model comprising input combination (v) has the highest R^2 value (0.907). Note that the R^2 term provides information for linear dependence between observations and corresponding estimates. Therefore, it is not always expected that R^2 is in agreement with performance criteria such as the RMSE. For example, in the case of two time series such as (Xi = 1,2,3, . . .,10; Yi = 20,40, 60,. . .,200) the R^2 between these two series is equal to 1 whereas the RMSE value is quite high. An R^2 value equal to 1 does not guarantee that a model captures the behavior of the investigated time series. In the present study, the main model performance criterion is the RMSE. The best model is selected by considering this criterion. Accordingly, it can be said that the ANFIS model whose inputs are the Qt, Qt_1, St_1, St_2, and Rt performs the best among the eight input combinations in Table 7. The first three combinations use the stream flow inputs. In the models where only stream flows are the inputs, the ANFIS model whose inputs are the current and one previous stream flow (input combination (ii)) has the best accuracy from the RMSE, MAE and R^2 viewpoints. It was observed that the inclusion of 2-day previous stream flow in the model (input combination (iii)) reduced the model performance. Input combinations (iv)–(vi) were obtained by adding the previous suspended sediment values into the input combination (ii). An improvement in the simulation performance is expected by adding the previous suspended sediment values into the input combinations, since the flow measurements are taken together with the suspended sediment values at the same cross-section of the river (Alp and Cigizoglu, 2007). In the models comprising both stream flows and suspended sediments as the inputs, the ANFIS model whose inputs are the current and one previous stream flow and two previous suspended sediments (input combination (v)) had the best accuracy according to the RMSE, MAE and R^2 statistics. Input combinations (vii) and (viii) were obtained by adding the rainfall values into the input combination (v). It is evident that the inclusion of 1-day previous rainfall in the model (input combination (viii)) reduced the model performance.

Table 7. The final architectures and RMSE, MAE and R2 statistics of the ANFIS models for the test phase

	NF model inputs	NF structure (number of membership functions)	RMSE (mg/l)	MAE (mg/l)	R2
(i)	Qt	6 gauss	282	110	0.819
(ii)	Qt, Qt_1	2 and 2 gauss	242	82	0.892
(iii)	Qt,Qt_1, Qt_2	2, 2 and 2 triangular	276	94	0.850
(iv)	Qt, Qt_1, St_1,	2, 2 and 2 triangular	227	68	0.875
(v)	Qt,Qt_1, St_1, St_2	2, 2, 2 and 2 triangular	223	58	0.907
(vi)	Qt, Qt_1, St_1, St_2, St_3	2, 2, 2, 2 and 2 triangular	248	64	0.836
(vii)	Qt, Qt_1, St_1, St_2, Rt	2, 2, 2, 2 and 2 triangular	214	60	0.890
(viii)	Qt, Qt_1, St_1, St_2, Rt, Rt_1	2, 2, 2, 2, 2 and 2 triangular	252	71	0.770

A comparison of the ANFIS model with the FFBP, RBF, GANN, MLR and SRC models is seen in Table 8. From that the table, the GANN model had the smallest RMSE (55 mg/l) and MAE (17 mg/l) and the highest R^2 (0.995) for the training phase. In the test phase, however, the ANFIS model had the smallest RMSE (215 mg/l) and MAE (58 mg/l) and the highest R^2 (0.905). The GANN model also had better accuracy than the other ANN approaches. There was consistency in training and test phase in the GANN. From the table, it can be deduced that the GANN model memorizes the training data. All the ANN models had better performances than the SRC model in both training and test periods.

The sediment peak-estimates obtained by the models and the corresponding observed values are compared in Table 9. From the table, the ANFIS model's peak-estimates were much closer to the observed values than those of FFBP, RBF, GANN, MLR and SRC models. All models underestimated the peak values. The ANFIS had the best accuracy (4) and the SRC had the worst accuracy (29) in terms of mean absolute relative errors (MARE) statistics of the peak-sediment values.

Table 8. The training and testing performances of the ANFIS, FFBP, RBF, GANN, MLR and SRC models in suspended sediment estimation

Models	Training phase			Test phase		
	RMSE (mg/l)	MAE (mg/l)	R^2	RMSE (mg/l)	MAE (mg/l)	R^2
ANFIS	154	51	0.965	215	58	0.905
FFBP	110	64	0.987	253	71	0.889
RBF	178	78	0.963	279	88	0.873
GANN	55	17	0.995	225	62	0.894
MLR	188	75	0.885	309	103	0.745
SRC	235	108	0.867	325	112	0.739

Table 9. The comparison of the ANFIS, FFBP, RBF, GANN, MLR and SRC peak-estimations for the test phase

Observed sediment peak (>500 mg l^{-1})	ANFIS	FFBP	RBF	GANN	MLR	SRC	Relative error (%)					
							ANFIS	FFBP	RBF	GANN	MLR	SRC
592	570	537	488	561	455	490	-4	-11	-22	-6	-30	-21
612	574	564	478	567	498	445	-7	-9	-28	-8	-23	-38
655	599	601	524	674	455	500	-9	-9	-25	3	-44	-31
731	745	870	866	768	544	910	2	16	-35	5	-35	20
836	795	555	651	784	687	461	-5	-5	-29	-7	-21	-82
871	856	564	534	819	598	604	-2	-54	-63	-6	-46	-45
920	890	825	801	857	715	765	-4	-12	-15	-8	-29	-21
990	973	919	909	945	1150	1130	-2	-8	-9	-5	14	13
1050	1035	988	974	1015	918	920	-2	-7	-8	-4	-15	-15
1100	1085	1174	1008	1165	1004	1185	-2	7	-10	6	-10	8
1150	1180	1247	1202	1125	1015	1195	3	8	5	-5	-14	38
1175	1155	1098	1352	1150	1482	1298	-2	-7	13	-2	21	10
						MARE (%)	4	13	22	6	26	29

The estimation of total sediment load obtained from the estimated suspended sediment concentration values was also considered for comparison due to its importance in reservoir management. Table 10 displays the total estimated sediment amounts in test period. An estimated total sediment load of 810.25 ton according to The ANFIS model was 775.48 ton, with an underestimation of 4.2%, while the FFBP, RBF, GANN, MLR and SRC models, respectively, computed total sediment load as 668.11, 610.33, 735.24, 587.89 and 514.55 ton, with underestimations of 17.5%, 24.6%, 9.2%, 27.4% and 36.5%, respectively. The estimate of the ANFIS model was closest to the observed value. SRC model had the worst estimate. GANN model had the best result compared with the other ANN models.

The results were also tested by using one-way analysis of variance (ANOVA) and t-test for verifying the robustness (the significance of differences between the model estimates and observed values) of the models. Both tests were set at a 95% significant level.

Differences between observed and estimated values were considered significant when the resultant significance level (p) was lower than the 0.05 value by use of two-tailed significance levels. The statistics of the tests are given in Table 11. The ANFIS model produced the smallest testing values (0.3531 and 0.5983) with the corresponding highest significance level (0.5641) for the ANOVA and t-test, respectively. According to the test results, it is obvious that the ANFIS is more robust (the similarity between the observed suspended sediments and ANFIS estimates are significantly high) in estimating suspended sediment concentration than the other methods. The GANN and FFBP models are better than the RBF, MLR and SRC.

Table 10. Estimated total sediment amounts in test period

	Observed	ANFIS	FFBP	RBF	GANN	MLR	SRC
Estimate (ton)	810.25	775.48	668.11	610.33	735.24	587.89	514.55
Relative error (%)		4.2	17.5	24.6	9.2	27.4	36.5

Table 11. Analysis of variance and t-test for suspended sediment concentration

Method	ANOVA		t-Test	
	F-statistic	Resultant significance level	t-statistic	Resultant significance level
ANFIS	0.3531	0.5641	0.5983	0.5641
FFBP	0.6049	0.4448	0.7041	0.4331
RBF	2.5217	0.1181	1.5617	0.1179
GANN	0.4432	0.5732	0.6082	0.5502
MLR	3.0042	0.1237	2.6687	0.1189
SRC	7.1106	0.0075	2.6874	0.0071

It was obvious that ANN and ANFIS models were comparable in terms of prediction accuracy. However, the ANFIS models performed better than ANN models. The temporal variations of the observed and predicted SSC using ANN, NF, MLR and SRC for testing period in both stations are shown in Figures 4 to 9. Moreover, the suspended sediment load predictions were plotted against observed SSC for both stations.

As it is raised from Figures 4 to 11, ANFIS and ANN models came up with better results for SSC prediction rather than the MLR and SRC models. In both stations, the predicted values of SSC by ANFIS and ANN models were in good agreement with the observed time series, while the SRC model presented poor results and significantly underestimated the peaks. The ANFIS model consistently underestimated the peaks, whereas the ANN model consistently underestimated or overestimated the high amount of SSC occurrence in compression to ANFIS models in both stations. The magnitudes of low, medium, and high SSC predictions by ANFIS models were closer to the observed values in comparison with the other models. On the other hand, ANFIS results were closer to the 45° straight line in the scatter plots compared with the other models in both stations; especially in the Dalaki River Station.

The main reason for this superior treatment is concealed in its structure. It not only uses the advantage of the simplifying function of fuzzy reasoning, but also uses the self-learning ability of neural networks with the strong capability of eliminating pseudo signals (noise). SRC technique utilizes all data as a regression method. In training set, aside from some exceptional peaks, other values were relatively low; therefore, this technique underestimates the extreme values of SSC.

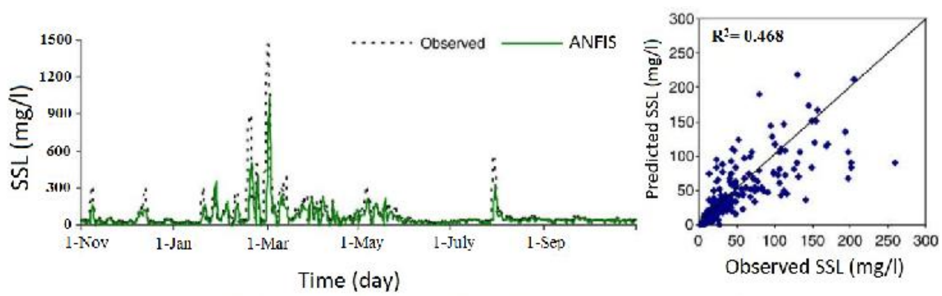

Fig. 4. SSL (Suspended Sediment Load) prediction by ANFIS model for Dalaki River Station in testing period

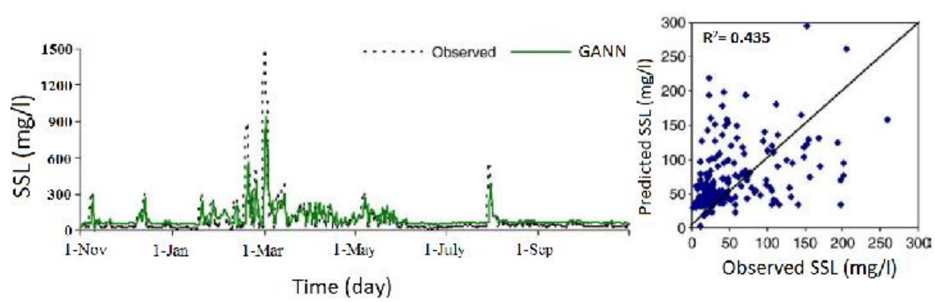

Fig. 5. SSL (Suspended Sediment Load) prediction by GANN model for Dalaki River Station in testing period

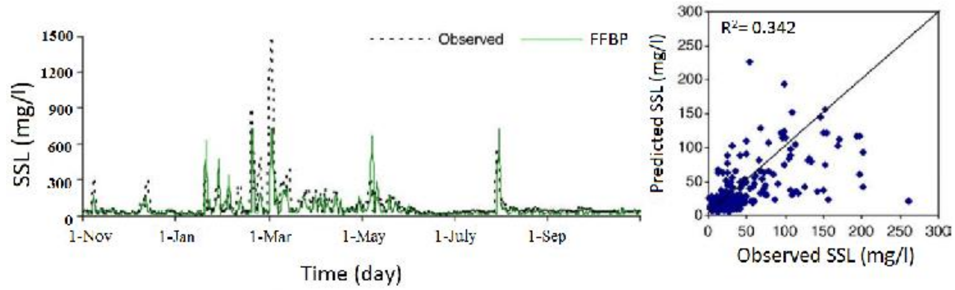

Fig. 6. SSL (Suspended Sediment Load) prediction by FFBP model for Dalaki River Station in testing period

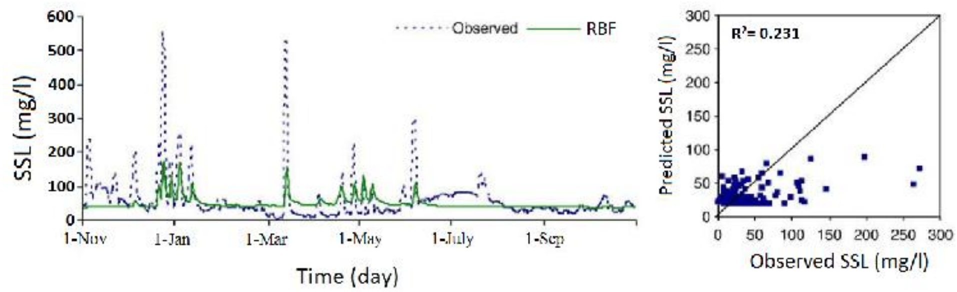

Fig. 7. SSL (Suspended Sediment Load) prediction by RBF model for Dalaki River Station in testing period

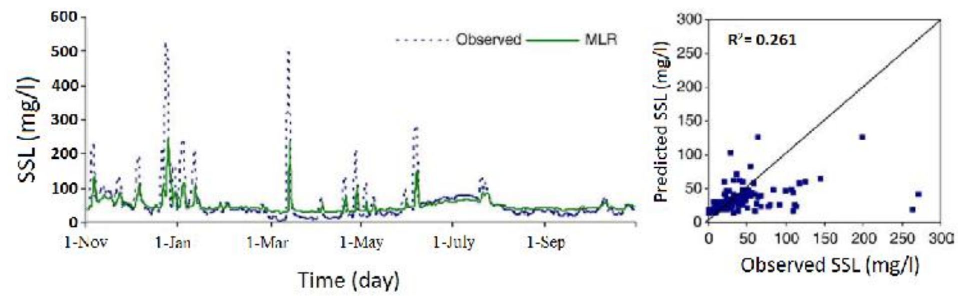

Fig. 8. SSL (Suspended Sediment Load) prediction by MLR model for Dalaki River Station in testing period

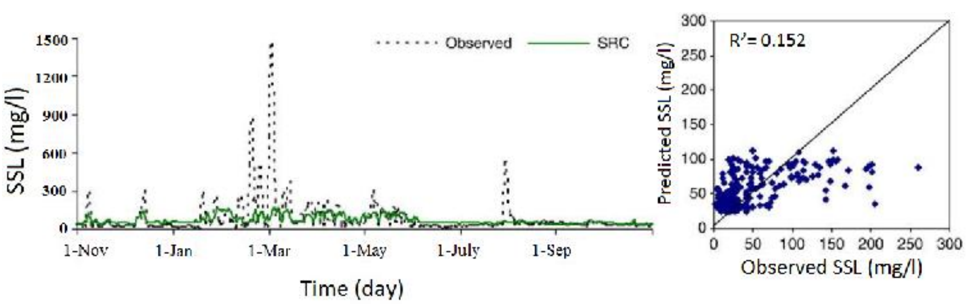

Fig. 9. SSL (Suspended Sediment Load) prediction by SRC model for Dalaki River Station in testing period

7. Conclusion

In the current study, suspended sediment concentrations were estimated by an adaptive neuro-fuzzy and three different neural network approaches using different combinations of hydrometeorological variables (stream flow and rainfall) and antecedent suspended sediment concentrations. The first section of study dealt with the use of several input combinations, including daily stream flow and rainfall of current and previous days and suspended sediment concentration of previous days as inputs to the ANFIS model to estimate current suspended sediment concentration. From the results, the ANFIS model whose inputs were current stream flow and rainfall, with one previous stream flow and two previous suspended sediment values had the best accuracy. In the second part of the study, the accuracy of the ANFIS model was compared with three different ANN computing techniques, GANN, FFBP and RBF in order to ascertain the best input combination obtained in the first part of the study. The MLR and SRC models were also considered for the comparison. The comparison results revealed that the ANFIS model performed better than the ANN models, MLR and SRC models in daily suspended sediment concentration estimation. The ANN models also provided better estimates than the MLR and SRC. According to the SRC models, the suspended sediment concentration was related only to the stream flow. However, the current study demonstrated that the current suspended sediment concentration apart from being dependent on the stream flow at the current time, was also dependent on the rainfall and suspended sediment concentration at the previous periods. The main advantages of using ANFIS and ANN methods are their flexibility and ability to model nonlinear relationships. Among the ANNs methods, in general, the GANN model was found to be slightly better than those of the FFBP and RBF methods in setting up suspended sediment concentration-hydrometeorological relationship.

Overall, the ANFIS model seems to be more adequate than the ANN models, together with the MLR and SRC for the process of establishing a rating relationship between suspended sediment and flow. Such problems frequently arise in a nonlinear manner. When a rating curve is built, the suspended sediment is related only to the current discharge. However, the current suspended sediment is not only dependent on the current discharge but also on the previous suspended sediment and discharges. The main advantages of using ANNs are their flexibility and ability to model nonlinear relationships. Mathematically, an ANN may be treated as a universal approximator (ASCE Task Committee, 2000). This technique has already become a prospective research area with great potential due to simple formulation and the ease of application. However, there are some disadvantages of ANN method. The network structure is hard to determine and it is usually determined using a trial and error approach, i.e., sensitivity analysis (ASCE Task Committee, 2000; Kisi, 2004b). Its training algorithm has the danger of getting stuck into local minima, etc. The ability of an ANN to extrapolate is limited when the input values in the prediction phase are far from the domain of the training data set. In this sense, an ANN is not very capable when it comes to extrapolation. An ANN model has a major drawback compared to physically based models, in that a new input variable that was not used in the training phase cannot be introduced to the model in the prediction phase, i.e., the number of input variables should be the same during the training and prediction phases (Sha, 2007; Dogan *et al*., 2008). On the contrary, the ANFIS models combine the transparent, linguistic representation of a fuzzy system with the learning ability of the ANN. Therefore, they can be trained to perform an input/output mapping just as with an ANN, but with the additional benefit of being able to provide the set of rules on which the model is based. This gives further insight into the process being modeled (Sayed *et al*., 2003).

This observation would be of much use in hydrological modeling studies where estimates of sediment values are not available. The model can be integrated as a module in general hydrological analysis models. In order to improve the current research, using the presented techniques to predict the suspended sediment load on the second, third or other following days, and modeling suspended sediment load process by considering other variables (e.g. temperature or precipitation intensity) are suggested. Furthermore, as a plan for the study, the presented approaches can be used to simulate monthly and event based SSC time series.

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