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Case Study

BASIN SUSPENDED SEDIMENT PREDICTION USING SOFT COMPUTING AND CONVENTIONAL APPROACHES IN INDIA

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ABSTRACT
The sediment modelling is one of the most important topics in water resources planning, development and management on sustainable basis. The Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS) and sediment rating curve (SRC) have been the efficient techniques for sediment modelling and forecasting. Gamma test (GT) is one of the non-linear modelling tools whereby an appropriate combination from input parameters can be investigated for modelling the output data as well as establishing a smooth model. This study was undertaken to develop and evaluate the applicability of the ANN, ANFIS and SRC models by way of training and testing of developed models during monsoon period (June to September) for Anandpur and Champua watersheds of Baitarani basin in the Keonjhar District, Orissa state of India. The best input combination of discharge and sediment were identified using the Gamma Test for the simulation of sediment yield, respectively. The following statistical indices such as mean squared error (MSE), coefficient of efficiency (CE), and coefficient of correlation (r), were applied to test the performance of the developed ANN, ANFIS and SRC models. The predicted sediment concentration using ANN and ANFIS models were found to be the best performing models for Anandpur and Champua watersheds. It was clearly evident that SRC models fit very poorly for the dataset under study.

KEYWORDS: Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System, sediment rating curve and Gamma test.

INTRODUCTION

Estimation of suspended sediment load from watershed is of utmost importance in the soil and water conservation practices in the watershed and in relation to several engineering topics, such as erosion around structures, backfilling of dredged channels, pollution, channel navigability reservoir filling, hydroelectric-equipment longevity, fish habitat, river aesthetics and scientific interests. Sediment rating curves (SRC) are largely used to estimate the sediment transport in river. However, traditional SRC are not able to provide adequately accurate results. A SRC is a relation between the sediment and 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. The sediment load process is a highly nonlinear and complex system. However, the empirical regressions, despite of their inability to represent successfully, the nonlinear complex system have been widely used. Another way to represent the complex sediment behavior is to assume that the processes governing sediment yield are to be stochastic and thus can be described by a stochastic process and associated probability distributions. It appears necessary that nonlinear methods such as artificial neural networks (ANN) and adaptive neuro fuzzy inference system (ANFIS), which are suited to complex nonlinear models, be used for the analysis of real world temporal data. The ANN and ANFIS are capable to model any arbitrarily complex nonlinear process that relates sediment load to continuous hydro-meteorological data (Kisi, O. 2005; Asadiani and Slotani, 2008; Nourani, 2009; Rajaee *et al.*, 2009; Cobaner *et al*., 2009; Feyzolahpour *et al*., 2012; Mustafa *et al*., 2012 and Demirci and Baltaci, 2013).

Recently, because of these problems, researchers are looking for simpler, cheaper and easier methods to obtain a relationship between sediment load and water discharge and they are beginning to use nonlinear models such as artificial intelligence techniques to solve nonlinear problems. In this paper, (a) investigate the soft computing techniques and conceptual techniques for modeling the complex sediment process, and (b) investigate the suitable inputs variable for study area. It seems necessary to use nonlinear models such as artificial neural networks (ANN) and adaptive neuro-fuzzy inference system (ANFIS), which is developed for estimating daily sediment load for Baitarani basin in the Keonjhar District Orissa state of India. These techniques are also suited to the complex non-linear models and cope with these difficulties and complexities. The artificial neural networks (ANN) approach has been applied to many branches of science. The approach is becoming a strong tool for providing civil and environmental engineers with sufficient details for design purposes and management practices. Motivated by successful applications in modeling nonlinear system behavior in a wide range of areas, ANN has been applied in hydrology and hydraulics. ANN have been used for rainfall-runoff modeling, sediment modeling, flow predictions, flow/pollution simulation, parameter identification, and modeling nonlinear/ input-output time series (ASCE, 2000a; Kisi, 2005; Rajaee *et al*., 2011; Vafakhan, 2013; Nourani *et al*., 2014; Nourani *et al*., 2015 and Rezaei and Fereydooni, 2015). Nagy *et al.* (2002) estimated that the natural sediment discharge in rivers in terms of sediment concentration by ANN model gives better results compared to several sediment transport formulas. Dogan *et al*. (2005) used artificial neural network (ANN) and fuzzy logic (FL) for predicting monthly suspended sediment load of Sakarya River in Turkey. It was observed that the FL gave better results than the ANN model. In this paper it seems necessary that nonlinear models such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS), is used to develop suspended sediment load estimation. The Gamma test is used to compute appropriate input variable. This technique is also suited the complex non-linear models and cope with these difficulties and complexity. Comparison results revealed that artificial intelligence techniques and conventional technique in estimation of daily suspended sediment load. Rajaee *et al*. (2011) further compared ANN, combined wavelet transform and ANN (WANN), MLR, and SRC models' performance in predicting daily SSL modeling at a gauging station on the Iowa River (Wapello, IA). They found the WANN model to closely fit observed SSL, and outperform all other models: the Nash–Sutcliffe model efficiency coefficient (NSE) for the WANN model was 0.81, compared to 0.67, 0.60, and 0.39 for the ANN, MLR, and SRC models, respectively, Using GP, adaptive neuro-fuzzy inference system (ANFIS), ANN and SVM models. Kisi et al. (2012) modeled daily SSL at two stations (Pineville and Barbourville, KY) on the Cumberland River. They found the GP model to outperform the other models in estimating daily SSL. Comparing the sediment yield prediction ability of a physically-based model (Soil and Water Assessment Tool, SWAT) and a data-driven model (multilayer perceptron ANN) for the Nagwa agricultural watershed in Jharkhand, India. Kermani *et al*. (2016). Three different ANN model algorithms were tested [gradient descent, conjugate gradient and Broyden–Fletcher–Goldfarb–Shanno (BFGS)], along with four different SVR model kernels [linear, polynomial, sigmoid and Radial Basis Function (RBF)]. The ability of artificial neural network (ANN) and support vector regression (SVR) models to forecast/estimate daily suspended sediment concentrations was evaluated and compared to that of traditional multiple linear regression (MLR) and sediment rating curve (SRC) models.

METHODOLOGY

Artificial neural networks (ANN)

The ANN is a flexible mathematical structure patterned after the biological nervous system. The feed-forward multi-layer perceptron (MLP) among many ANN paradigms is by far the most popular, which usually uses the technique of error back-propagation to train the network configuration. The neural network used in this study has a three-layer network consisting of an input layer, a hidden layer, and an output layer shown in Fig 1. For a network training method, the back-propagation algorithm (BPA) introduced by Rumelhart and McClelland (1986) can effectively train the network for non-linear problems. Also, the activation function consists of a sigmoid function in the hidden layer and a linear function in the output layer. It has been reported that ANNs with this configuration are the most commonly used form, as they have improved extrapolation ability (ASCE 2000a; Cigizoglu, 2004; Gharde *et al.*, 2015; Jain 2001 and Partal, 2009). The mathematical expression of the MLP is as follows:

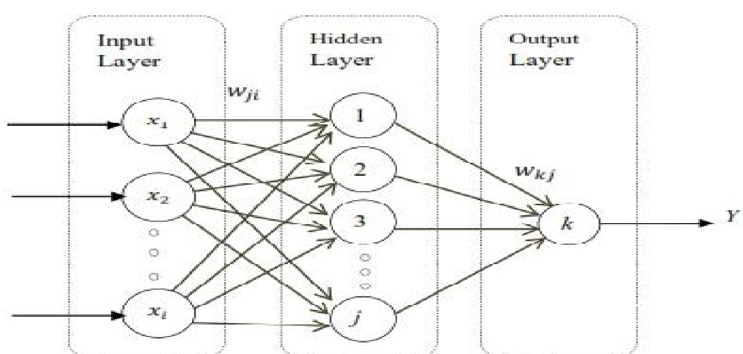

FIGURE 1: Single hidden layer feed-forward neural network

The most widely used learning algorithm for training the neural networks is the back-propagation algorithm. Back-propagation algorithm (BP) is a supervised algorithm which adjusts the connection weights and biases in the backward direction. It is an optimization procedure based on gradient descent to minimize the total error between the desired and actual outputs. The input data are multiplied by the initial weights, then the weighted inputs are added by simple summation to yield the net input to each neuron.

$$Net = w_1x_1 + w_2x_2 + \cdots + w_{ji}x_i \quad \text{…. (1)}$$

$$Net = \sum_{i=1}^{N} w_{ji}x_i \quad \text{…. (2)}$$

Where,

X_i is the input to any neuron, w_{ji} is the connection weighted between j^{th} layer to i^{th} layer, N is the number of inputs and Net is the net for j^{th} neuron. The output of k^{th} node of the hidden layer b_k is given as:

$$b_j = f(net) \quad \text{.... (3)}$$

Where $f(net)$ is the activation function, example a tanh activation function . This can be represented as:

$$b_j = \frac{e^{(net)} - e^{(-net)}}{e^{(net)} + e^{(net)}} \quad \text{.... (4)}$$

The error calculated at the output layer is propagated back to the hidden layers and then to the input layer, in order to determine the updates for the weights. The mean sum of square error E for a single input-output pair data set is given as:

$$E = \frac{1}{2}\sum_{i=1}^{N}(c_i - d_i)^2 \quad \text{.... (5)}$$

Where,

E is the Total error, c_i is the observed or calculated output at i^{th} node and d_i is the target or desired output at i^{th} node.

During the training process a set of pattern examples is used. Each example consisting of a pair with the input and corresponding target output. The patterns are presented to the network sequentially in an iterative manner, the appropriate weight corrections being performed during the process to adapt the network to the desired behavior. This repeating continues until the connection weight values allow the network to perform the required mapping. Each presentation of the whole pattern set is named an epoch. After this the term repetition will refer either to a pattern presentation or to a complete epoch depending on the situation. The generalized delta rule is used to calculate the values of the local gradients. Each weight update is defined as:

$$\Delta w_{ji}(n) = \eta \delta_j a_i \quad \text{.... (6)}$$

and the equations of the generalized delta rule used to calculate the values are

$$\delta_j = a_j(1 - a_j)(t_j - a_j) \quad \text{.... (7)}$$

$$\delta_j = (1 - a_j)\sum_{k=1}^{N_{i=1}} \delta_k w_k \quad \text{.... (8)}$$

The weight update for the output units can be calculated using directly available values since the error measure is based on the difference between the desired t_j and actual a_j values. However that measure is not available for the hidden neurons. The solution is to back-propagate the j values layer by layer through the network.

Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS is functionally equivalent to fuzzy inference systems. Specifically, the ANFIS system of interest here is functionally equivalent to the Sugeno first-order fuzzy model (Jang, 1997). Figure 2 shows the Sugeno-fuzzy reasoning system for this Sugeno-fuzzy model. An ANFIS is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. ANFIS learning employs two methods for updating MF parameters: (1) backpropagation for all parameters (a steepest descent method), and (2) a hybrid method consisting of back propagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output MFs (Kisi and Tombul, 2013). The first-order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules, can be given as (Sanikani and Kisi, 2012)

One of the most popular integrated systems is adaptive neuro-fuzzy inference system (ANFIS) which has shown promising results in modelling nonlinear time series. In ANFIS, Takagi-Sugeno type fuzzy inference system is used. The output of each rule can be a linear combination of input variables plus a constant term. The final output is the weighted average of each rule's output. Basic ANFIS architecture that has two inputs X and Y and one output Z is shown in Fig. 3.6. The rule base contains two Takagi-Sugeno if-then rule as follows:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$- (9)

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$ (10)

Where A_n and B_n are fuzzy sets in the antecedent; p_n, q_n and r_n are polynomial parameters of n^{th} rule (also called the consequent parameters).

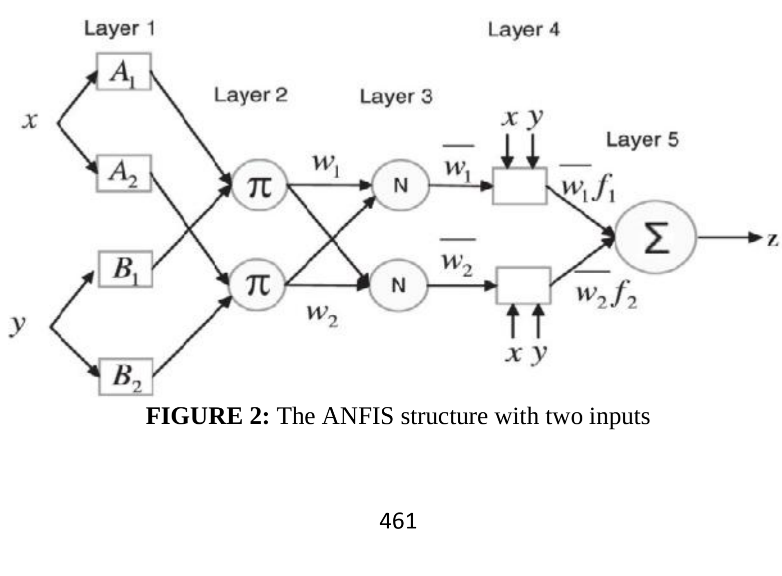

FIGURE 2: The ANFIS structure with two inputs

The node functions in the same layer are the same as described below:

Layer 1: Every node I in this layer is a square node with a node function as:

$O_i^1(x) = \mu A_i(x)_i$ for i = 1, 2 …. (11)

$O_i^1(x) = \mu B_i - 2(x)_i$ …. (12)

where x is the input to i^{th} node, A_i (or i−2 B) is a linguistic label (such as "small" or "large") connected with node, and O_i is the membership grade of a fuzzy set A_i such as Gaussian and Generalized bell. Based on the problem, different membership functions can be applied. For instance, if the membership function of i^{th} node is a generalized bell function, the output of i^{th} node in the first layer defines as:

$$\mu A_i(x) = \frac{1}{1+|(x-c)/a|^{2b}} \quad …. (13)$$

And the Gaussian function

$$\mu A_i(x) = e^{-\left(\frac{x-c_i}{a_i}\right)} \quad …. (14)$$

Where (a_i, b_i, c_i) are premise parameters that change the shape of the membership function.

Layer 2: Every node in this layer is a fixed node labeled as II, whose output is the product of all incoming signals**:**

$$O_i^2 = W_i = \mu A_i(x)_i \quad \mu B_i(x)_i \qquad i = 1, 2 \quad …. (15)$$

Layer 3: Every node in this layer is a fixed node labeled N. The i^{th} node calculates the ratio of the rule's firing strength of the sum of all rule's firing strengths:

$$O_i^3 = W_i = \frac{W_i}{(W_1 - W_2)} \qquad i = 1, 2 \quad …. (16)$$

Layer 4: Ever node i in this layer is a square node with a node function:

$$O_i^4 = \bar{W}_i f_i = \bar{W}_i(p_i x + q_i y + r_i) \quad …. (17)$$

where, $\bar{W_i}$ is a normalized firing strength from layer 3 and {p_i, q_i, r_i} is the parameter set of this node. Parameters in this layer are referred to as "consequent parameters".

Layer 5: The single node in this layer is a fixed node labeled sigma that computes the overall output as the summation of all incoming signals:

$$O_i^5 = \sum_i \bar{W}_i f_i = \frac{\sum_i W_i f}{\sum_i W_i} \quad …. (18)$$

This layer is called as the output nodes in which the single node computes the overall output by summing all the incoming signals and is the last step of the ANFIS. In this way the input vector was fed through the network layer by layer.

Sediment rating curve (SRC)

A considerable part of sediment in rivers is transported as suspended load. As the finest fraction of the SSL is often a non-capacity load, it cannot be predicted using stream power related sediment transport models. Instead, empirical relations such as SRCs are often applied. The establishment of a SRC is an important problem in hydrology. Since the measurement of sediment is costly and time consuming, the discharge is usually measured daily. The primary data which are collected to determine the suspended sediment load and discharge of a river are Q and SSL. Q is the instantaneous river discharge which is measured with a current meter or is taken from a stage-discharge curve for the gauging station. SSL is the instantaneous suspended sediment load in tons per day. The instantaneous suspended sediment discharge is computed from Q and SSL. The sediment rating curves generally represent a functional relationship of the form:

$SSL = aQ^b$ …. (19)

Where SSL is suspended sediment load and Q is stream discharge. a and b values for a particular stream are determined from data by establishing a linear regression between (log SSL) and (log Q).

Gamma Test

GT is one of the non-linear modelling tools whereby an appropriate combination from input parameters can be investigated for modelling the output data as well as establishing a smooth model. GT estimates the minimum mean square errors which is obtainable in continuous non-linear models with unseen data. Suppose there is a set of data as the following:

$$((x_1 \dots x_n)y) = (X, y) \quad ….. (20)$$

Where $X = (x_1 \dots x_n)$ is the input vector in the output vector's areas of y and $C \in R^n$. If the relationship is established between the set members:

$$y = f(x_1 \dots x_n) + r \quad ….. (21)$$

in which r is a random variable. GT is an estimate for the output variance of a non-smooth model. According to K [i, k], Gamma Test includes a list of k (1≤ k ≤ p) the k^{th} neighbor for each vector X (1 ≤ i ≤ M). Delta function calculates the mean squared distance of the k^{th} neighbor.

$$\delta_M(k) = \frac{1}{M}\sum_{i=1}^{M}\left|[X_{n[i.k]} - X_i]\right|^2 \quad …. (22)$$

In which | | indicates Euclidean distance, corresponding gamma function is as:

$$\gamma_M(k) = \frac{1}{2M}\sum_{i=1}^{M}[Y_{n[i.k]} - Y_i]^2 \quad …. (23)$$

Where $Y_{N[i,k]}$ is the value of y corresponding to the k^{th} neighbor of X_i in the equation (22). In order to calculate gamma the linear regression is fitted from p spot to values of $\delta_M(k)$ and $\gamma_M(k)$.

$$\gamma = A\delta + gamma \quad …. (24)$$

The intercept of this line $\delta = 0$ indicates the gamma value and $\gamma_M(k)$ is equal to the errors variance. Provided that n is the number of the input variables, the combination 2^n - 1 of would be among them. Reviewing all these combinations takes a lot of time. GT can identify the most effective variable in modeling and the best combination of the input variables. In addition, M test can also identify the length of training period of the prediction model to establish a smooth model.

Area detail and data

The Baitarani is one of the important east flowing rivers of peninsular India, flowing eastward and joining the Bay of Bengal shown in Fig 3.0. The total catchment area of this basin is 10,982 km^2 given in table 1.0. More than 93% of the catchment area falls in Orissa. The basin receives most of the rainfall from the South-West monsoons during the period from June to October. The sediment and discharge data is observed at Champua and Anandpur site of central water commission. The 12 years data from 2001to 2012 of Champua site and 38 years data from 1974 to 2012 of Anandpur site are used in present study. The Anandpur 38 years data split in two sets first 30 year data for training and another 8 years for testing. Similarly the Champua site 12 years data divided into set first ten year for training and another two year for testing.

TABLE 1: Location of site

Site Name	Drainage Area (Km^2)	Latitude	Longitude
Champua	2412	22º03'57"N	85º40'56"E
Anandpur	8570	21º12'34"N	86º07'23"E

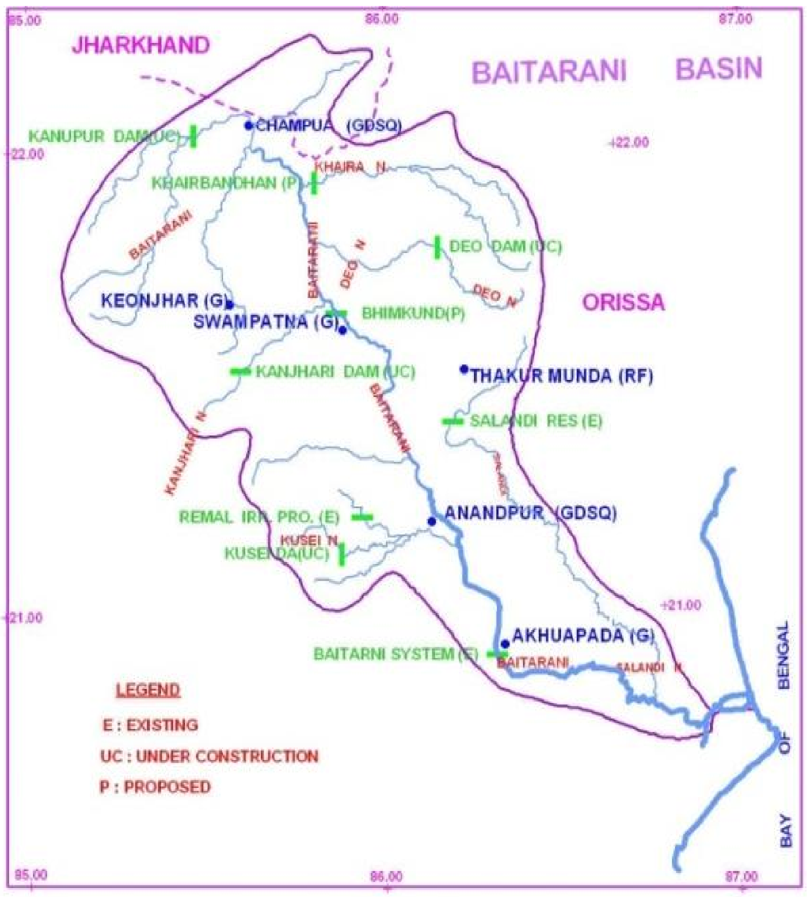

FIGURE 3: Map of Baitarani Basin

PERFORMANCE EVALUATION OF MODELS

Mean square error (MSE)

The mean square error is used to measure the prediction accuracy of a model. The mean square error (MSE) is determined by following relationship:

$$MSE = \frac{\sum_{i=1}^{n}(S_t - S_p)^2}{n} \qquad \text{…. (25)}$$

where, S_t is ith observed values of daily suspended sediment load, S_p is predicted values of daily suspended sediment load and n is the number of observations.

Correlation coefficient (r)

The Correlation Coefficient (r) is an indicator of degree of closeness between observed and predicted values and provides the level of variance explained between observed and predicted.

$$r = \left[\frac{\sum_{i=1}^{n}\{(S_t - \bar{S}_t)(S_p - \bar{S}_p)\}}{\sqrt{\sum_{i=1}^{n}(S_t - \bar{S}_t)^2}\sqrt{\sum_{i=1}^{n}(S_p - \bar{S}_p)^2}}\right] \qquad \text{…. (26)}$$

Where $\bar{S}_t$ is average of the observed daily suspended sediment load series and $\bar{S}_p$ is average of predicted daily suspended sediment load series.

Coefficient of efficiency (CE)

The Coefficient of efficiency is one for perfect match between observed and predicted values. Similarly CE value equal to zero indicates that the model predictions are equal to mean of observed data series. The Coefficient of efficiency is determined by using the following equation:

$$CE = 1 - \frac{\sum_{i=1}^{n}(S_t - S_p)^2}{\sum_{i=1}^{n}(S_t - \bar{S}_t)^2} \quad \text{.... (27)}$$

RESULT

Model input selection using GT

The Gamma test is a nonlinear continuous modeling and analysis tool, which estimates the minimum mean square error (MSE) during modeling the unseen data and allows for examining the input/output relationship in a numerical data set. It can help to find the required size of data and best input combination to achieve a particular target output. The Gamma test was first introduced by Agalbjrn, *et al*., 1997 and after that many researchers discussed this issue in detail (Chuzhanova, *et al*., 1998; Jones, *et al*., 2002 and Tsui *et al*., 2002). Gamma Test predicts the minimum achievable modeling error before the modeling. Suppose n is the variables influencing on occurrence of a phenomenon; 2^n-1 meaningful combination would be established from the input variables. In this study, Different combinations of input data were evaluated to assess their influence on the SSL prediction by GT as shown in Table 2.0 and 3.0.

TABLE 2: Identifying the most effective variable based on GT of Champua site

Different combinations	Mask	Gamma	SE
Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, S_{t-1}, S_{t-2}, S_{t-3}, S_{t-4}	111111111	0.09667	0.00574
All - Q_t	011111111	0.12034	0.00629
All - Q_{t-1}	101111111	0.09929	0.00647
All - Q_{t-2}	110111111	0.09511	0.00590
All - Q_{t-3}	111011111	0.09143	0.00460
All - Q_{t-4}	111101111	0.09239	0.00339
All - S_{t-1}	11110111	0.09806	0.00605
All - S_{t-2}	11111011	0.09605	0.00583
All - S_{t-3}	11111101	0.09587	0.00573
All - S_{t-4}	111111110	0.09163	0.03663

TABLE 3: Identifying the most effective variable based on GT of Anandpur site

Different combinations	Mask	Gamma	SE
Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, S_{t-1}, S_{t-2}, S_{t-3}, S_{t-4}	111111111	0.0322	0.0144
All - Qt	011111111	0.0601	0.0130
All - Q_{t-1}	101111111	0.1142	0.0152
All - Q_{t-2}	110111111	0.0593	0.0157
All - Q_{t-3}	111011111	0.0557	0.0162
All - Q_{t-4}	111101111	0.0217	0.0117
All - S_{t-1}	11110111	0.0581	0.0131
All - S_{t-2}	11111011	0.0547	0.0196
All - S_{t-3}	11111101	0.0545	0.0194
All - S_{t-4}	111111110	0.0252	0.0125

TABLE 4: Determination of the best combination

Different combinations	Mask	Gamma	SE
Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}, S_{t-3}	111001110	0.09768	0.006054
Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}	111001100	0.09187	0.005473
Q_t, Q_{t-1}, Q_{t-2}, S_{t-1},	111001000	0.09419	0.005623
Q_t, Q_{t-1}, S_{t-1},	110001000	0.09898	0.006121
Q_t, Q_{t-1}, S_{t-1}, S_{t-2}	110001100	0.09649	0.005918
Q_t, Q_{t-1}, S_{t-1}, S_{t-2}, S_{t-3}	110001110	0.09478	0.005667

As the results indicated in Table 2, among nine existence parameters, Q_t has the greatest influence on suspended sediment load (St) at Champua site because this parameter from the modeling increases the Gamma value (C) and Standard Error (SE). Moreover, omitting the parameters Qt-3, Qt-4 and St-4 had no significant influence on gamma value. The minimum value of gamma static was observed when all available input data sets were used. Similarly, parameter Qt-1has greatest influence on suspended sediment load (St) at Anandpur site. Also, parameter Qt-4 and St-4 has no significant indicated in Table 3.0 After identifying the most effective variable, the best input combination should be determined for prediction.

TABLE 5: Determination of the best combination

Different combinations	Mask	Gamma	SE
$Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, S_{t-1}, S_{t-2}, S_{t-3}$	111101110	0.03768	0.009554
$Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, S_{t-1}, S_{t-2}$	111101100	0.03180	0.008273
$Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}\ S_{t-1},$	111101000	0.03410	0.008824
$Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}$	111001000	0.03081	0.007821
$Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}$	111001110	0.02768	0.007766
$Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}, S_{t-3}$	111001110	0.02547	0.007197

According to the results of GT the combination of 111001100 (five inputs and an output) is selected as the best combination for Champua site. The statistic values associated with the GT in best combination is shown in Table 4.0 Small gamma value shows that data would achieve better possibility of results in modeling by the provided combination. Low SE value is also another reason for better results can be expected. Similarly according to the results of Gamma test the combination of 111001110 is the best combination of inputs and output for Anandpur site of Baitarani basin shown in Table 5.0. Furthermore, in order to review the reliability of the results obtained from the GT method, various combinations from input parameters were evaluated using GT so as to determine the best combination among the remaining variables for predicting the SSL note that in selecting the combinations, it has been tried to choose different combinations including parameters which have been recognized in prediction using Gamma Test as the most effective input parameters ($Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}$) for Champua site and ($Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}, S_{t-3}$) for Anandpur site . These combinations are illustrated in Table 3 and 4 along with their gamma values and SE. The results indicate that the best input combination from the variables is when required discharge and sediment are used. Low gamma value shows that data would achieve better possibility of results in modeling by the provided combination. Therefore, the best input combination determined with GT.

ANN, ANFIS and SRC models result

The results in terms of various performance statistics from all the models are presented in Table 6.0 of Anandpur site. Analyzing the results during training and testing, it can be observed that the SRC model performed the worst with MSE, r and CE statistics of 0.000187, 0.876 and 0.845 during training and 0.000112, 0.901 and 0.870 during testing respectively, while the performances of the ANN model obtained result MSE, r and CE statistics of 0.000019, 0.967 and 0.941 during training period and 0.000011, 0.982 and 0.974 during testing period were comparable. The ANFIS model obtained the best results in term of MSE, r and CE statistics of 0.000016, 0.975 and 0.956 respectively during training period and 0.000010, 0.991 and 0.982 respectively during testing period. Analyzing the results during testing, it can be observed that the ANFIS model trained using Gaussian membership functions the best outperformed all other models. Thus, it can be said that when the overall performance is considered, the ANFIS model trained using Gaussian membership functions performed the best, the ANN model trained using back propagation algorithm performed the moderate result and SRC model having worst performance. The qualitative performance was evaluated by visual observation Fig. 4.0 to 6.0.

TABLE 6: Statistical performance evaluation of Anandpur site from ANN, ANFIS, SRC models

Model	Training			Testing		
	MSE	r	CE	MSE	r	CE
ANN	0.000019	0.967	0.941	0.000011	0.982	0.974
ANFIS	0.000016	0.975	0.956	0.000010	0.991	0.982
SRC	0.000187	0.876	0.845	0.000112	0.901	0.870

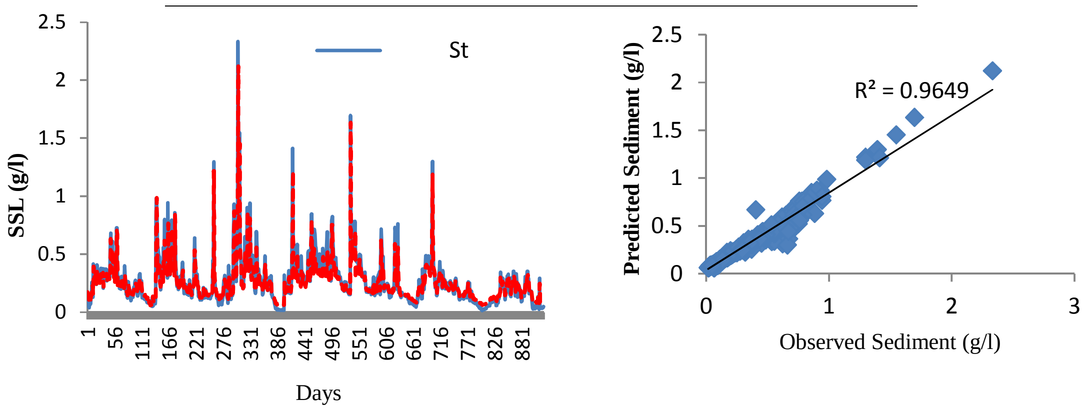

FIGURE 4: Comparison of observed (St) and predicted (S_p) daily suspended sediment load and their corresponding scatter plot during testing period for ANN model

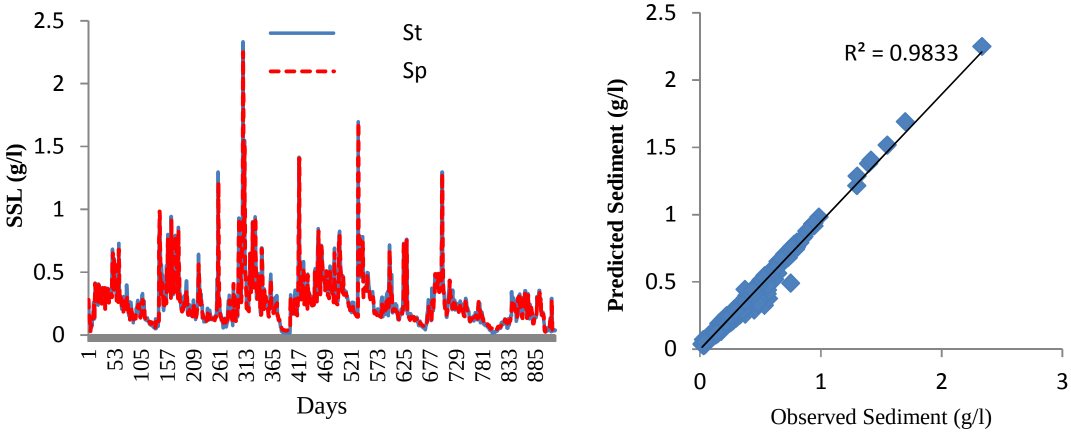

Figure 5: Comparison of observed (St) and predicted (S_p) daily suspended sediment load and their corresponding scatter plot during testing period for ANFIS model

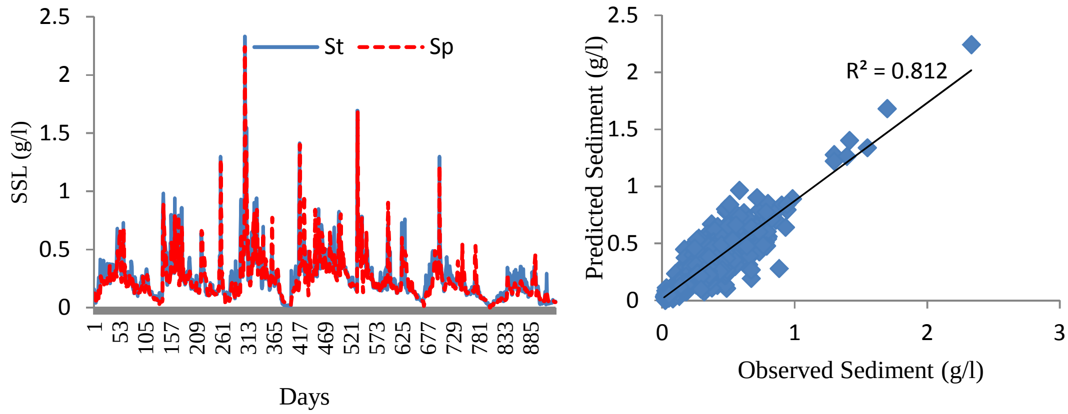

FIGURE 6: Comparison of observed (St) and predicted (S_p) daily suspended sediment load and their corresponding scatter plot during testing period for SRC model

The performance evaluation of the sediment yield model was carried out on the basis of visual comparison of observed and computed sediment graphs as well as by statistical computing the criteria such as MSE, r and CE statistics. The comparisons between the observed and predicted sediment graphs are shown in Figs. 7 to 9 for Champua watershed, respectively. The graphical as well as the statistical criteria used (Tables 7.0) show that the ANFIS based model produce the sediment graphs closer to the observed one as compared to the ANN and SRC model. Thus, the shape of the sediment graphs is very well preserved in case of ANFIS based model in testing events. The ANFIS model was found to be best results with MSE, R, and CE statistical of 0.000013, 0.975 and 0.961 and similarly during training period 0.000010, 0.993 and 0.987 during the testing.

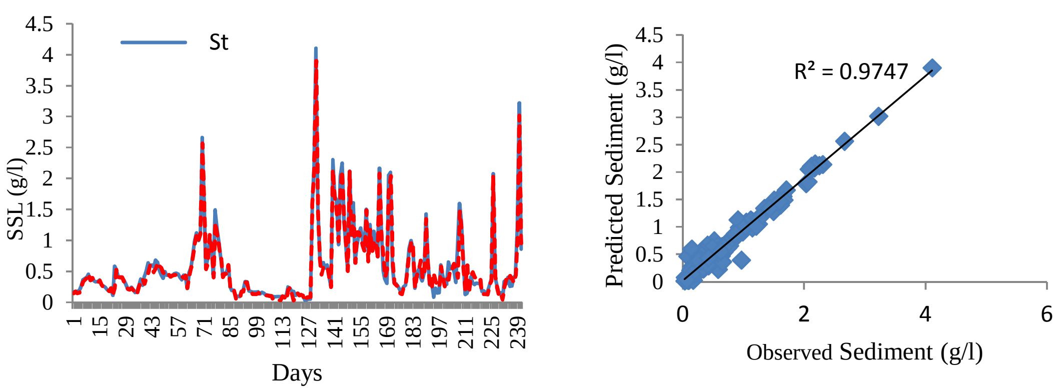

FIGURE 7: Comparison of observed (St) and predicted (S_p) daily suspended sediment load and their corresponding scatter plot during testing period for ANN model

TABLE 7: Statistical performance evaluation of Champua site from ANN, ANFIS, SRC models

Model	Training			Testing		
	MSE	r	CE	MSE	r	CE
ANN	0.000015	0.971	0.956	0.000010	0.987	0.979
ANFIS	0.000013	0.975	0.961	0.000010	0.993	0.987
SRC	0.000171	0.869	0.856	0.000103	0.897	0.878

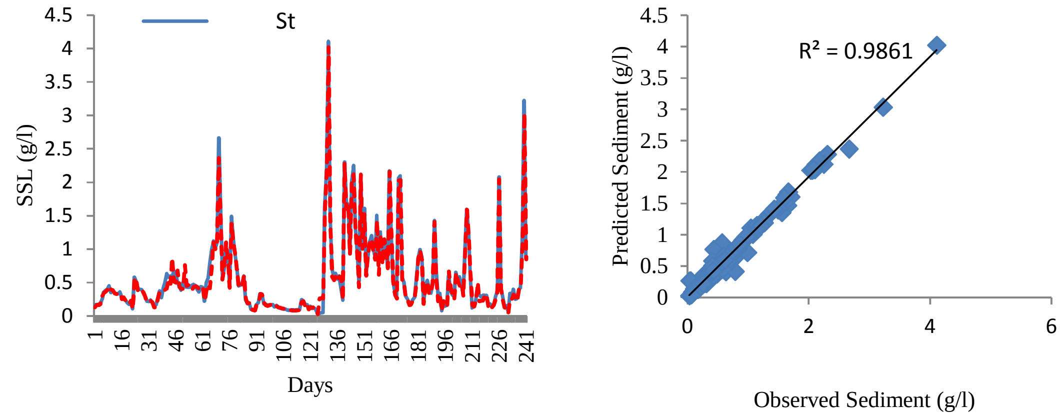

FIGURE 8: Comparison of observed (St) and predicted (S_p) daily suspended sediment load and their corresponding scatter plot during testing period for ANFIS model

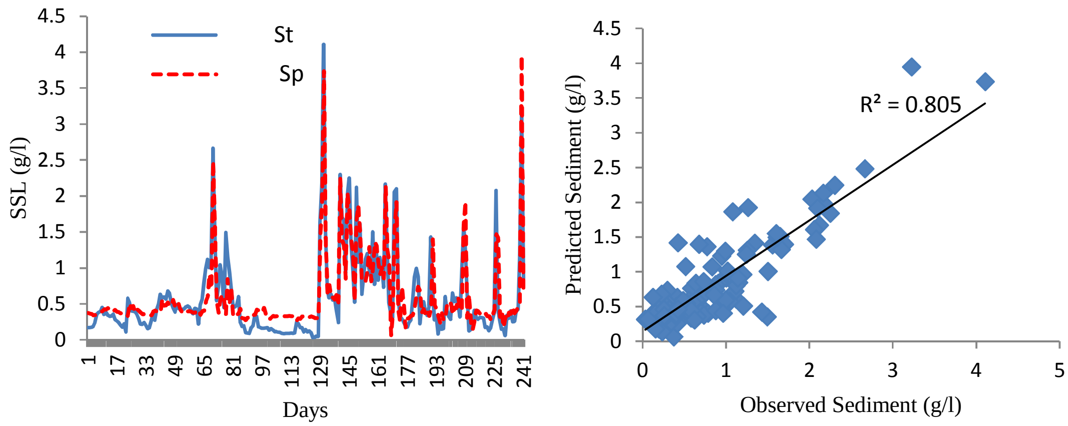

FIGURE 9: Comparison of observed (St) and predicted (S_p) daily suspended sediment load and their corresponding scatter plot during testing period for SRC model

CONCLUSION

In the present study, an effort was made to compare the soft computing and sediment rating curve models for prediction of suspended sediment load. It was seen that including flow and suspended sediment concentration or sediment discharge in a nonlinear function could not perform a good prediction of sediment load in special conditions. Meanwhile, the use of two soft computing methods, (ANN) and (ANFIS) and one conventional method, SRC are employed to estimate sediment load. ANN structure with the number of nodes in hidden layer via Levenberg–Marquardt algorithms has improved the simulation results and therefore was sufficient to obtain satisfactory performance in suspended sediment load prediction. The comparison results indicated that ANFIS model has superior performance than ANN and SRC models in estimating daily sediment load. The results clearly indicate that the ANFIS and ANN can used for sediment modeling in Baitarani Basin. From the results it can say that soft computing technique was better performed than the conventional technique. Gamma test (GT) is one of the non-linear modelling tools whereby an appropriate combination from input parameters can be investigated for modeling. A wide variety of standard statistical performance evaluation measures were employed to evaluate the performances of various ANN, ANFIS and SRC models developed.

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