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Modeling suspended sediment concentration using multilayer feedforward artificial neural network at the outlet of the watershed

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■ **ABSTRACT :** Eight multilayer feedforward artificial neural network based models were developed to predict daily suspended sediment concentration for the Baitarani river at Anandpur gauging station using daily discharge and daily suspended sediment concentration. The 30 years data (June 1977 to September 2006) used in this study was divided into two sets viz. a training set (1977-1996) and a testing set (1997-2006). Artificial neural networks (ANN) models were calibrated by using multilayer feedforward back propagation neural networks with sigmoid activation function and Levenberg-Marquardt (L-M) learning algorithm. The performance of the developed models was evaluated qualitatively and quantitatively. In qualitative evaluation of models, the observed and the computed suspended sediment concentration were compared using sediment hydrographs and scatter plots during testing period. Akaike's information criterion (AIC), correlation co-efficient (r), mean square error (MSE), root mean square error (RMSE), minimum description length (MDL), co-efficient of efficiency (CE) and normalized mean square error (NMSE) indices were used for quantitative performance evaluation of the models. Results on the basis of qualitative and quantitative evaluation indicate that M-6 model with (7-5-5-1) network architecture is better than all models at Anandpur station and it was also found that artificial neural network based model is better than physics based models such as sediment rating curve and multiple linear regression.

■ **KEY WORDS :** Multilayer feedforward artificial neural networks, Levenberg-Marquardt (L-M) learning algorithm, Sigmoid activation function, Suspended sediment concentration modeling, Sediment rating curve, Multiple linear regression.

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Soil, one of the earth materials, is very important to sustain the life on earth. Serious concern in many parts of the world is experienced due to accelerated erosion which was caused by environmental disturbance directly or indirectly by human beings. Main contributing factors for occurrence of such problems are rapid urbanization, expansion of agriculture and deforestation which change land use pattern and this asking for the development, conservation and utilization of soil and water resources in such a way that high productivity and sustainability is ensured. Soil erosion not only reduces the quality of water but also creates the flooding problem, where it deposits. Much emphasis was given to resolve complex water resource management problems in which key component for study was to develop deep understanding of sediment load estimation in river. Various factors were responsible for causing variability in sediment load among all factors rainfall as well as stream flow was to significant factors which effect suspended load concentration (Jie and Yu, 2011). The quality of runoff and sediment yield also depend on the rainfall intensity, duration, initial soil moisture, land use and land cover, slope of the watershed etc.

A great revolution has been observed in prediction and resolving hydrologic problems by various researchers when artificial neural networks were used as tool with any system theoretic model. Main character of black box was to simulate complex natural process and, therefore, it was considered of much significance when it was employed to solve different types of water resource problems. ANNs, one of the most popular soft computing techniques, are example of system theoretic models. They have been used to model water fluvial system in the field of engineering and applied hydrology. Model development is based upon input and output data and no understanding of physical laws are required. Non linear systems which cannot be modelled by traditional method can be modelled by ANN. ASCE (2000 a and b) gave concepts of ANN and its application in hydrology and its allied fields. In recent years, artificial neural networks based system theoretic models have been employed in solving hydrological and meteorological problems such as rainfall runoff modelling, runoff sediment modelling (Singh *et al.*, 2013; Rai and Mathur, 2008; Kisi *et al.*, 2012; Gharde *et al.*, 2015; Jain, 2001; Kermani *et al.*, 2016; Kumar *et al.*, 2016; Olyaie *et al.* 2015; Ghorbani *et al.*, 2013; Eisazadeh *et al.*, 2013; Shabani and Shabani, 2012; Kumar *et al.*, 2011 and Kisi, 2010), river flow estimation (Nayak *et al.*, 2004), evapo-transpiration process (Kuo *et al.*, 2011 and Khoob, 2008), optimization of water supply system, ecological and hydrological response assessment to climate change, modelling of reservoir inflow and operation, remediation of ground water and prediction of ground water quality, drought forecasting etc.

It was found that geomorphology based neural network is better than non geomorphology based neural network for sediment yield prediction (Sarangi and Bhattacharya, 2005). Imrie *et al.* (2000) enhanced the generalization through a supervised system to the extrapolation properties and cascade correlation learning architecture by using a suitable activation function. Dawson and Wilby (1998) explained behaviour of an artificial neural networks based rainfall runoff model. Danh *et al.* (1999) and Elshorbagy *et al.* (2000) predicted runoff by using two criterion *i.e.* fixed stopping criterion and independent variables, through feed forward error back propagation in ANN and then the model was compared with the results obtained through available conceptual models.

The main purpose of the present study is development, validation and performance evaluation of ANN models to estimate concentration of suspended sediment on daily basis for the Baitarani river at Anandpur station located at the outlet of the Baitarani river basin falling in the state of Odisha, India and comparison of best selected model with the physics based models such as SRC and MLR.

■ METHODOLOGY

Description of the study area :

The Baitarani river originates from the Guptaganga hills ranges near Mankarancho village and flows eastward and joins the Bay of Bengal. The maximum and minimum annual rainfall is 3094 mm and 642 mm, respectively, and average rainfall is 1187 mm.

The Baitarani river basin is located between $85^0 10'$ to $87^0 03'$ east longitudes and between $20^0 35'$ to $22^0 15'$ north latitudes. Most of the rainfall in the watershed is received from the South-West monsoons from June to September. About 80% of annual rainfall occurs during June to September. The total area of Baitarani river basin is 10982 sq. km (Fig. A).

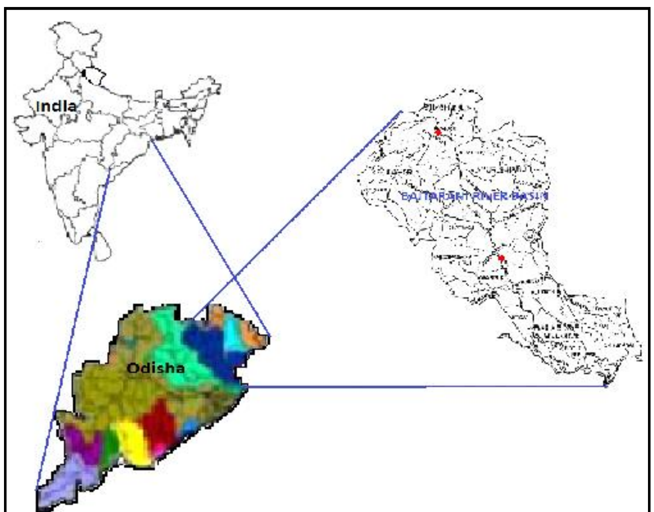

Fig. A : Location map of Baitarani river basin

Artificial neural networks :

Multilayer feedforward network :

One or more hidden layers are present in the multilayer feedforward neural networks. Its computation nodes are known as hidden neurons. The hidden layer intervenes between the input and the output in some useful manner. The network has the capability to take higher-order statistics by increasing one or more hidden layers, which is particularly valuable when the input layer has a large size. According to Churchland and Sejnowski (1992), the neural network obtains a global perspective, though it has local connectivity due to the extra set of synaptic connections.

The nodes where computation occurs are called computation nodes or neurons. There is no computation in the input layer, so the nodes of the input layer are not the neurons.

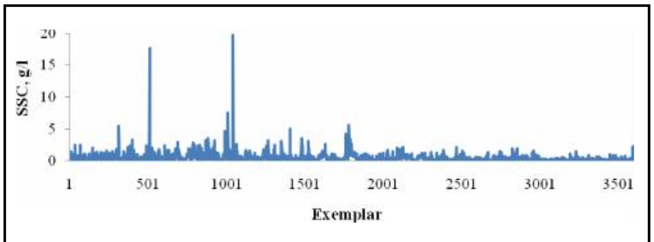

Fig. B : Daily SSC for monsoon season from 1977 to 2006 at Anandpur station on Baitarani river

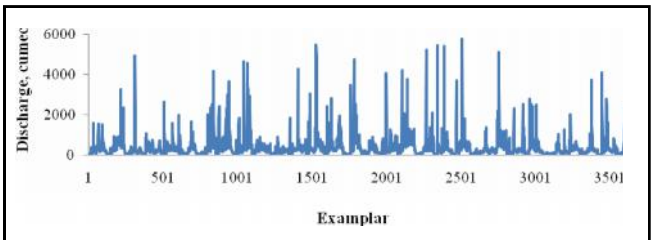

Fig. C : Daily discharge for monsoon season from 1977 to 2006 at Anandpur station on Baitarani river

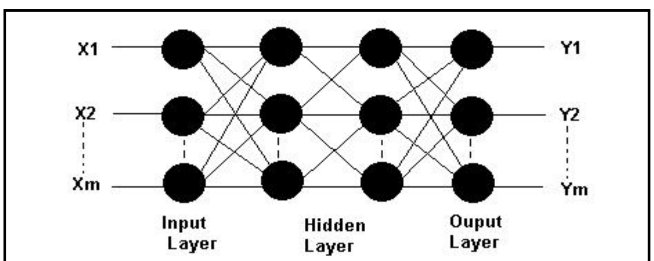

Fig. D : Multilayer feedforward networks

The input layer nodes which are source nodes of the neural network supply and elements of the activation pattern are called input vector, which constitute the input signals applied to the neurons in the second layer. The second layer output signals are used as input signals to the third layer, and so on for the rest of the network. The architectural graph in Fig. D illustrates the layout of a multilayer feed forward neural network for the case of two hidden layers.

Learning processes of artificial neural networks:

There are two types of training or learning mechanisms *i.e.* supervised and unsupervised. When a set of input pattern and its known output pattern is used to train the neural network, this type of learning is called supervised learning. In unsupervised learning the system learns on its own by finding regularities in the input space with the help of correlation and without direct feedback from the teacher or user.

In this study, supervised learning has been used. There are several algorithms for supervised learning in ANNs. Among these algorithms, back-propagation is the popular due to its simplicity and effectiveness. The back-propagation algorithm has emerged as the workhorse for the design of a multilayer perceptron (MLP). MLP is completed by using a back propagation algorithm that involves forward phase and backward phase.

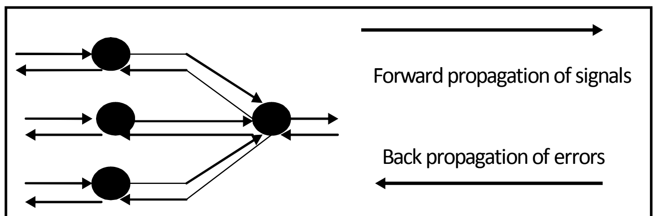

Fig. E : Directions of signal flow in an ANN

The error calculated at the output layer is sent back to the hidden layers and then passed on to the input layer, so that updates for the connection weights are determined the sum square error.

Activation functions :

The activation function or transfer function is a mathematical formula which used to find out the output of a processing element. The connections between the input layer and the middle layer contain weights as determined by training the system. In the present study, sigmoid activation function has been used. A sigmoid axon function having a S shape curve (sigmoid curve) as shown in Fig. F and defined by the eq. 4.

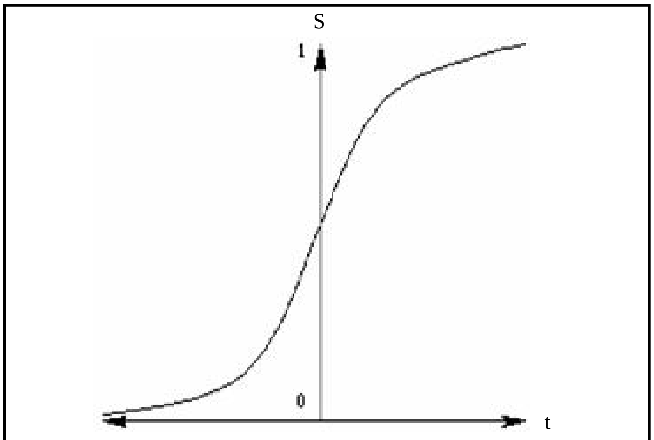

Fig. F : Sigmoid axon function

$$S(t) = \frac{1}{1+e^{-t}} \tag{1}$$

Multiple linear regression :

In multiple linear regression (MLR) equation, relationship between dependent variable and several independent variable by fitting in a linear equation. Regression analysis is commonly used to describe quantitative relationships between a dependent variable and one or more independent variables (Shirsath and Singh, 2010). MLR are used to model linear variables based on a least squares technique. However, MLR present some shortcomings and drawbacks in predicting nonlinear situations, given their nature of capturing strictly linear relations.

$$Y = b_0 + b_1X_1 + b_2X_2 + ...+ b_nX_n \tag{2}$$

where, Y is the dependent variable, b_0, b_1, b_2 ..... b_n are the regression co-efficients for the linear equation and X_1, X_2, ...X_n are the independent variables.

Sediment rating curve :

The SRC, generally follow the following form of relationship given in eq. 3.

$$St = a\ (Q_t)^b \tag{3}$$

where, a and b are the co-efficients, S_t is present day suspended sediment concentration and Q_t is present day discharge. The values of a and b for a particular stream are determined from data via a linear regression between log S_t and log Q_t. A major limitation of this approach is that it is not able to consider the hysteresis effect. In this study, the values of a and b are computed by using the least squares method (Jain, 2008 and Rajaee *et al.*, 2009)

Model development :

Standardization of raw data :

To avoid the possibility of a model from giving more importance to some variables as compared to others, data is standardized between certain constant values (Rai and Mathur, 2008). In this study, data have been standardized between 0 to +1 using the eq. 4.

$$x' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{4}$$

where, x' is the standardized value if the raw data value *x*, x_{max} and x_{min} are the maximum and minimum values of raw data value *x*, respectively.

Identification of input and output variables :

Input variables selection is a crucial step for model forecasting as they decide the structure of the ANN model and affect output of model. Several combinations of the discharge and suspended sediment concentration were tried to construct the proper input structure.

Development of artificial neural networks models :

After the identification of input and output variables, various artificial neural networks models were developed for the Anandpur station and the developed models for ANN are listed in Table A.

Training and testing of MLP-ANN models :

Data accounting from year 1977 to 1996 was used for model training and data accounting from year 1997 and 2006 was used for model testing for Anandpur station. In this study, the training of ANN models was done by using single and double hidden layers neural networks, sigmoid activation function, processing elements from 1 to 10 in both the hidden layers simultaneously, Levenberg-Marquardt learning rule, 0.001 training threshold with maximum 1000 number of epochs.

Table A : List of various ANN models for Baitarani river basin

Model	Output-input variables
M-1	$S_t = f\,(S_{(t-1)}, Q_t)$
M-2	$S_t = f\,(S_{(t-1)}, Q_t, Q_{(t-1)})$
M-3	$S_t = f\,(S_{(t-1)}, S_{(t-2)}, Q_t, Q_{(t-1)})$
M-4	$S_t = f\,(S_{(t-1)}, S_{(t-2)}, Q_t, Q_{(t-1)}, Q_{(t-2)})$
M-5	$S_t = f\,(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, Q_t, Q_{(t-1)}, Q_{(t-2)})$
M-6	$S_t = f\,(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, Q_t, Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)})$
M-7	$S_t = f\,(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, S_{(t-4)}, Q_t, Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)})$
M-8	$S_t = f\,(S_{(t-1)}, S_{(t-2)}, S_{(t-3)}, S_{(t-4)}, Q_t, Q_{(t-1)}, Q_{(t-2)}, Q_{(t-3)}, Q_{(t-4)})$

where, S_t, $S_{(t-1)}$, $S_{(t-2)}$, $S_{(t-3)}$, $S_{(t-4)}$, Q_t, $Q_{(t-1)}$, $Q_{(t-2)}$, $Q_{(t-3)}$ and $Q_{(t-4)}$ are present day suspended sediment concentration, one day lag suspended sediment concentration, two days lag suspended sediment concentration, three days lag suspended sediment concentration, four days lag suspended sediment concentration, present day discharge, one day lag discharge, two days lag discharge, three days lag discharge and four days lag discharge, respectively.

Performance evaluation of models :

Performance measures are used to indicate how well a model performs its tasks. The performance of the model can be measured qualitatively and quantitatively. In this study, sediment hydrographs and scatter plots are used for qualitative performance evaluation of models and the different performance evaluating indices were used for quantitative performance evaluation of models and discussed below;

Normalized mean square error (NMSE) :

$$\mathbf{NMSE} = \frac{\mathbf{PNMSE}}{\sum_{j=0}^{P} \frac{N \sum_{i=0}^{N} S_{cij}^{2} - \left(\sum_{i=0}^{N} S_{cij}\right)^{2}}{N}} \qquad (5)$$

Root mean square error (RMSE) :

$$\mathbf{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} \left(S_{ci} - S_{oi}\right)^{2}}{N}} \qquad (6)$$

Correlation co-efficient (r) :

Karl Pearson co-efficient of correlation has been used in this study. A positive correlation co-efficient indicates that the observed and computed values tend to go up and down together. If the variables go in opposite directions, it results in a negative correlation co-efficient.

$$r = \frac{\sum_{i=1}^{N}(S_{oi} - S_{om}) \sum_{i=1}^{N}(S_{ci} - S_{cm})}{\sqrt{\sum_{i=1}^{N}(S_{oi} - S_{om})^{2}}\ \sqrt{\sum_{i=1}^{N}(S_{ci} - S_{cm})^{2}}} \qquad (7)$$

Minimum description length (MDL) :

Rissanen's minimum description length (MDL), similar to the AIC, combines the error of model with the number of degree of freedom to find out the level generalization. The goal here, is to minimize this term.

$$\mathbf{MDL\ (k) = N\ ln\ (MSE) + 0.5\ k\ ln\ (N)} \qquad (8)$$

Akaike's information criterion (AIC) :

Akaike's information criterion (AIC) measures the trade off between training performance of the model and network size. The goal in this case is to minimize this term so that a network with the best generalization is produced.

$$\mathbf{AIC\ (k) = 2k + N\ ln\ (MSE)} \qquad (9)$$

Co-efficient of efficiency (CE) :

Co-efficient of efficiency computes the goodness of fit between the measured and the computed values of a model. An efficiency of 1 shows a perfect match between computed and measured values. An efficiency of 0 indicates that the model computed values are as accurate as the average of the measured data, whereas an efficiency less than zero shows that observed mean is a better computer than that of the model.

$$CE = 1 - \frac{\sum_{i=1}^{N}(S_{oi} - S_{ci})^{2}}{\sum_{i=1}^{N}(S_{oi} - S_{om})^{2}} \qquad (10)$$

where, S_{ci} and S_{oi} are the computed and measured suspended sediment concentration for i^{th} exemplar, S_{om} and S_{cm} are the mean of computed and observed suspended sediment concentration values, N is the total number of observations in the training or testing data set, k is the number of network weights, P is the number of output processing elements, S_{cij} is the computed output for i^{th} observations and at j^{th} processing element.

RESULTS AND DISCUSSION

The results obtained from the present investigation as well as relevant discussion have been summarized under following heads :

Qualitative performance evaluation of daily suspended sediment concentration models :

In this study, various artificial neural network architectures were applied using trial and error procedure and network architecture which were found to be best during testing and training periods at Anandpur station using qualitative evaluation are shown in Table 1.

Table 1 : Best selected network architecture for models at Anandpur station

Model	Network architecture	No. of epochs ran
M-1	2-7-7-1	23
M-2	3-9-9-1	22
M-3	4-4-4-1	26
M-4	5-10-10-1	32
M-5	6-8-8-1	35
M-6	7-6-1	22
M-7	8-4-4-1	22
M-8	9-5-5-1	35

The observed and the computed suspended sediment concentration for artificial neural networks based models were compared graphically using sediment hydrographs and scatter plots during testing period because during training period the model performance can be improved by over fitting the data and that can not be consider under selection of best models but model performance during testing period is independent of this.

Performance evaluation based on sediment hydrographs :

Sediment hydrographs for qualitative evaluation are shown in Fig. 1. It was observed from the sediment hydrographs that out of eight models, M-7 very closely predict the peaks accurately and rest of the models *i.e.* M-1, M-2, M-3, M-4, M-5, M-6 and M-8 over predict the peaks.

Performance evaluation based on scatter plots :

Scatter plots are shown in Fig. 4. The observations of scatter diagrams on the basis of best fit line and 1:1 line indicate that the suspended sediment concentrations are over predicted for smaller values of suspended sediment concentration and under predicted for larger values of suspended sediment concentration using M-1, M-4, M-5, M-6 and M-7 models and over predicting for M-2 and M-8 models. It was also observed for model M-7 that most of the suspended sediment concentration values are under predicted and very few suspended sediment concentration values are over predicted. The values of co-efficient of determination (R^2) for M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8 models are 0.986, 0.659, 0.670, 0.667, 0.673, 0.674, 0.703 and 0.571, respectively.

It is observed from the scatter plot of model M-1 that all the data points are very closely near to the line of best fit. Therefore, the M-1 model is found to be best in comparison to eight models for prediction of daily suspended sediment concentration at Anandpur station.

Quantitative performance evaluation of daily suspended sediment concentration models :

Performance evaluation indices for models during testing period at Anandpur station are given in Table 3. Based on the selected criteria, five artificial neural networks based models *i.e.* M-1, M-3, M-5, M-6 and M-7 were found to be performing better than out of the eight models. M-1 model had the minimum values of Akaike's information criterion (-11895.47), minimum description length (-11752.57), normalized mean square error (0.3050), and root mean square error (0.0071 g/l) and maximum values of co-efficient of efficiency (0.9994) and co-efficient of correlation (0.993) in comparison to M-3, M-5, M-6 and M-7 models. Therefore, the performance of the M-1 model was found to be best for prediction of daily suspended sediment concentration at Anandpur station. The order of models performance from best to worst for five selected models was found to be M-1 > M-7 > M-6 > M-5 > M-3.

On the basis of comparison between qualitative and quantitative evaluation for best model at Anandpur station, the M-1 model in which present day suspended sediment concentration (SSC) depends on the present day discharge and one lag day suspended sediment concentration with (2-7-7-1) network architecture *i.e.* 2 input variables, seven-seven neurons in first and second hidden layers and single output processing element is found to be best out of eight models.

Qualitative comparison of best ANN-MLP model with physics based models :

The observed and the computed suspended sediment concentration for artificial neural networks based models were compared graphically with the results of multiple linear regression analysis and sediment rating curve methods using sediment hydrographs and scatter plots during testing period.

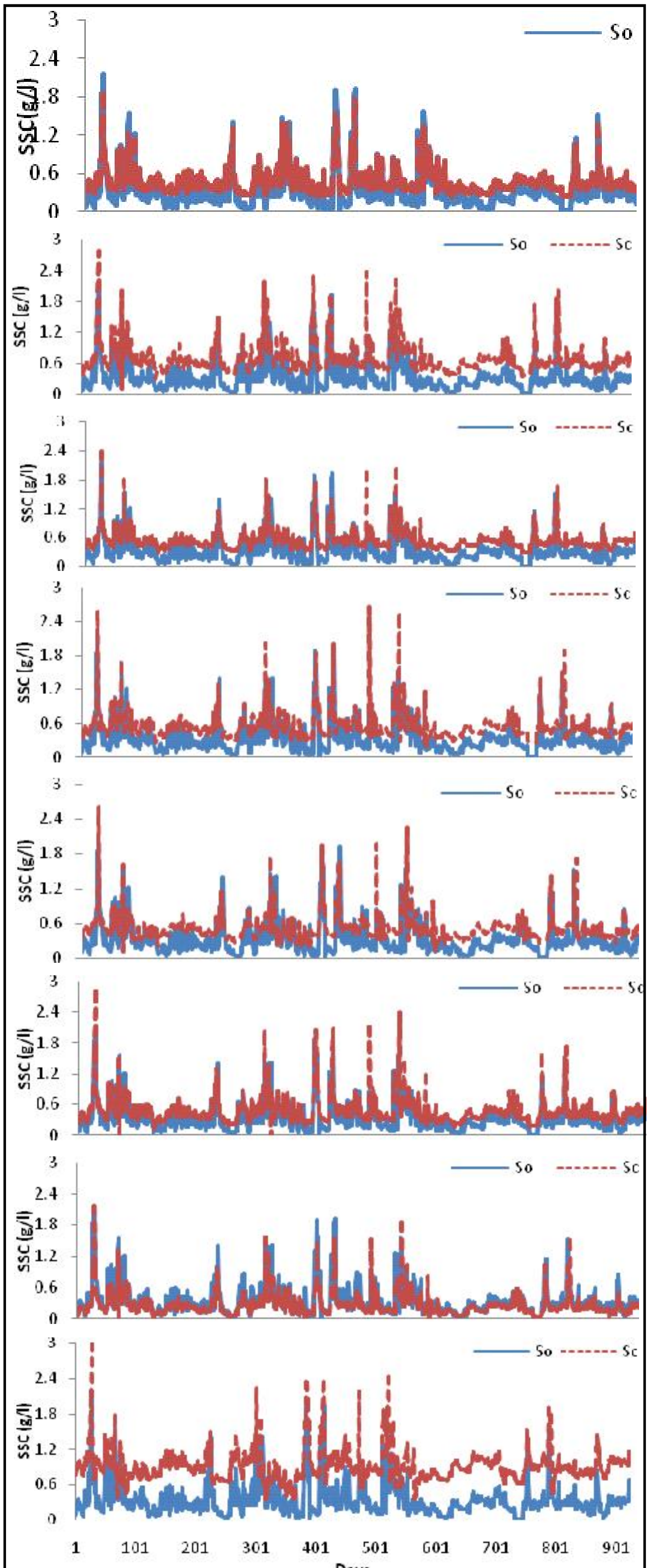

Fig. 1 : Observed (So) and computed (Sc) suspended sediment concentration from M-1 to M-8 models during testing period at Anandpur station

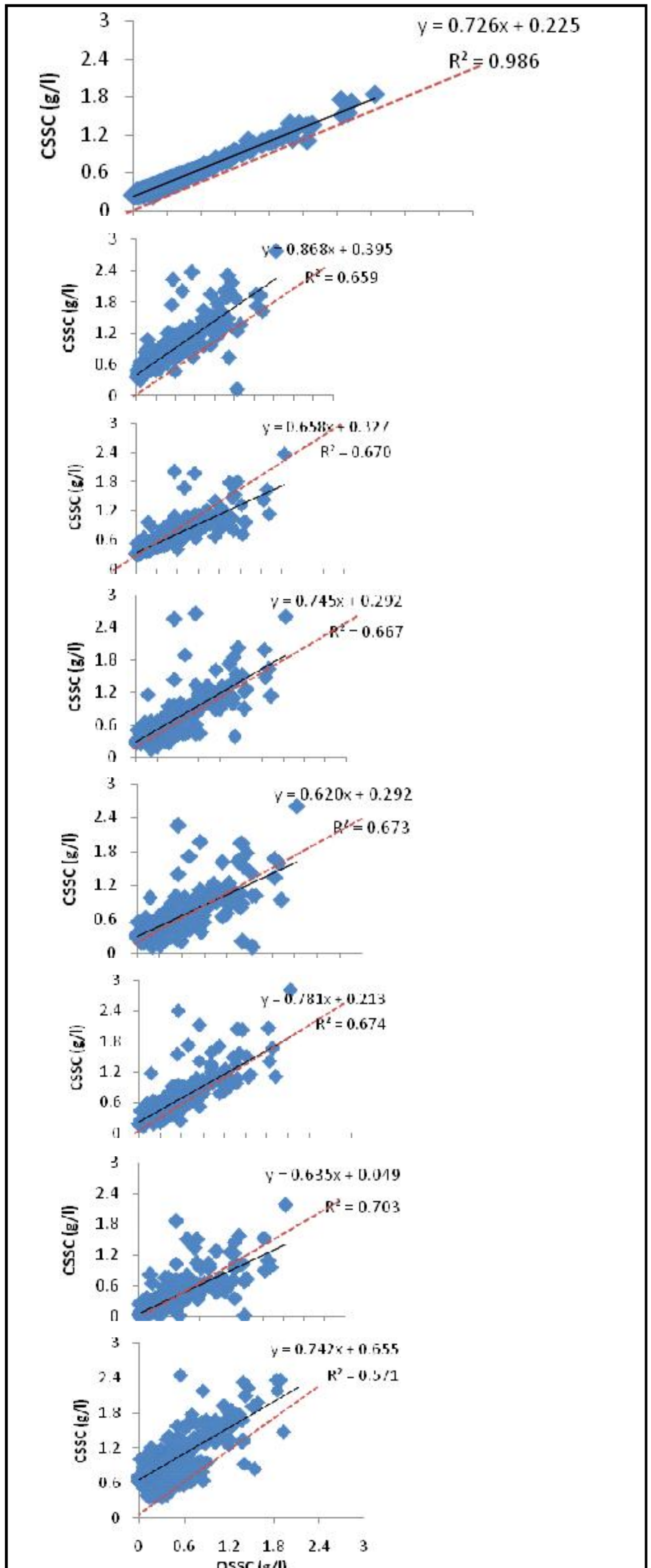

Fig. 2 : Scatter plots of suspended sediment concentration from M-1 to M-8 models during testing period at Anandpur station

Comparison based on scatter plots :

Scatter plots are plotted between computed suspended sediment concentration values on ordinate and their corresponding observed suspended sediment concentration values on the abscissa and are shown in Fig. 4. The observations of scatter diagrams on the basis of best fit line and 1:1 line (dotted line) indicate that the suspended sediment concentrations are over predicted for smaller values of suspended sediment concentration and under predicted for larger values of suspended sediment concentration for all the methods for M-1 model. It was also observed that the results of SRC are very worst to predict the SSC in comparison to other methods.

M-1 model of ANN-MLP nicely demonstrates that most of the data points are quite near the line of best fit in comparison to other methods. Therefore, ANN-MLP was found to be better than other methods for daily SSC prediction at Anandpur station. The values of co-efficient of determination (R^2) for ANN-MLP, MLR and SDR are 0.986, 0.345 and 0.287, respectively.

Comparison based on sediment hydrographs :

Sediment hydrographs are shown in Fig. 3. It was

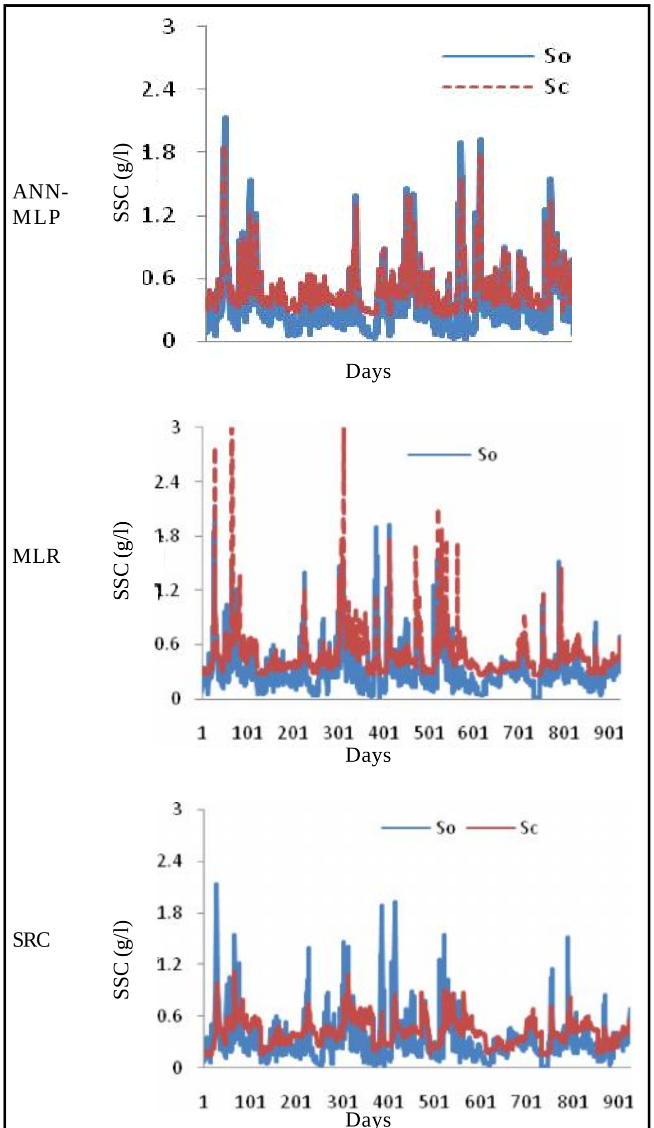

Fig. 3 : Observed (So) and computed (Sc) suspended sediment concentration of M-1 model during testing period at Anandpur station

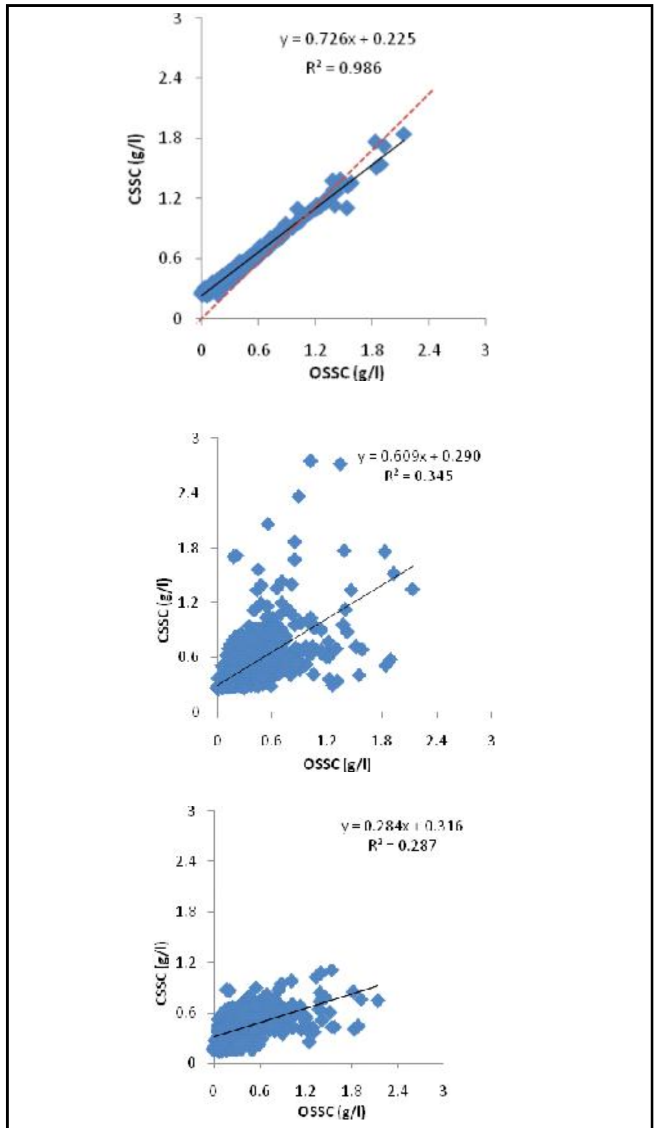

Fig. 4 : Scatter plots of suspended sediment concentration of M-1 model during testing period at Anandpur station

observed from sediment hydrograph of ANN-MLP which is very closely predicting the peaks accurately and found that it is best out of three sediment hydrograph. For multiple linear regression analysis and sediment rating curve, sediment hydrographs are over predicting the peaks. It was also observed that sediment hydrograph of multiple linear regression analysis is giving better result than sediment rating curve.

Quantitative comparison of best ANN-MLP model with physics based models :

Quantitative comparison is always considered to be effective in performance evaluation of the developed models and free from all personal biases which occur during qualitative evaluation. The values of indices for testing period at Anandpur station for all the methods are given in Table 3. The methods having higher values of co-efficient of efficiency (CE), co-efficient of correlation (r) and minimum values of root mean square error (RMSE) were considered as best methods. Based on the above criteria, ANN-MLP was found to be performing better than MLR and SDR.

Based on comparison among ANN-MLP, MLR and SDR for M-1 model at Anandpur station, ANN-MLP method has the maximum values of co-efficient of efficiency (0.9994), co-efficient of correlation (0.993) and minimum value of root mean square error (0.0071 g/l). The order of the methods from best to worst at Anandpur station was found to be ANN-MLP > MLR > SDR. Therefore, performance of the ANN-MLP based M-1 model was found to be best in comparison to other methods for prediction of daily suspended sediment concentration at Anandpur station.

On the basis of comparison between qualitative and quantitative evaluation for best method, it was found that ANN-MLP method is best out of MLR and SDR for prediction. Finally, ANN-MLP based M-6 model was found better than all the models and methods in this study for the prediction of daily SSC at Anandpur station.

Summary and conclusion :

Artificial neural networks based models were developed to predict daily suspended sediment concentration for the Baitarani river at Anandpur station using daily discharge and daily suspended sediment concentration. The 30 years data (June 1977 to September 2006) used in this study was divided into two sets viz. a training set (1977-1996) for model calibration and a testing set (1997-2006) for validation of models. Eight models for Anandpur station were developed by using various combinations of discharge and SSC and the performance of the developed models was evaluated qualitatively by visual observations and quantitatively using various Performance evaluation indices. Furthermore, A comparison was made between ANN-MLP, MLR and SDR methods for the selection of best method.

There are following conclusions were drawn from

Table 2 : Performance evaluation indices of ANN-MLP models for testing period Anandpur station of Baitarani river basin

Model	Network architecture	Testing					
		RMSE (g/l)	r	CE	NMSE	AIC	MDL
M-1	2-7-7-1	0.0071	0.993	0.9994	0.3050	-11895.47	-11752.57
M 2	3-9-9-1	0.0173	0.828	0.9962	1.7983	-9624.84	-9399.61
M-3	4-4-4-1	0.0114	0.833	0.9984	0.8078	-10793.12	-10717.01
M 4	5-10-10-1	0.0118	0.831	0.9982	0.8275	-10479.72	-10183.04
M-5	6-8-8-1	0.0110	0.835	0.9985	0.7122	-10754.75	-10529.52
M-6	7-6-1	0.0095	0.838	0.9989	0.5599	-11216.42	-11121.67
M-7	8-4-4-1	0.0078	0.839	0.9992	0.3699	-11714.22	-11613.25
M-8	9-5-5-1	0.0268	0.753	0.9909	4.3884	-8644.41	-8503.06

Table 3 : Quantitative comparison of ANN-MLP based M-1 model during testing period

Method	RMSE (g/l)	r	CE
ANN-MLP	0.0071	0.993	0.9994
MLR	0.3161	0.587	-0.2645
SRC	0.2505	0.536	0.2061

the results of the study;

– It was observed from the sediment hydrographs that out of eight models, M-7 very closely predict the peaks accurately and rest of the models *i.e.* M-1, M-2, M-3, M-4, M-5, M-6 and M-8 over predict the peaks.

– The observations of scatter diagrams on the basis of best fit line and 1:1 line indicate that the suspended sediment concentrations are over predicted for smaller values of suspended sediment concentration and under predicted for larger values of suspended sediment concentration using M-1, M-4, M-5, M-6 and M-7 models and over predicting for M-2 and M-8 models. It was also observed for model M-7 that most of the suspended sediment concentration values are under predicted and very few suspended sediment concentration values are over predicted. The values of co-efficient of determination (R^2) for M-1, M-2, M-3, M-4, M-5, M-6, M-7 and M-8 models are 0.986, 0.659, 0.670, 0.667, 0.673, 0.674, 0.703 and 0.571, respectively.

– It is observed from the scatter plot of model M-1 that all the data points are very closely near to the line of best fit. Therefore, the M-1 model is found to be best in comparison to eight models for prediction of daily suspended sediment concentration at Anandpur station.

– In Quantitative evaluation, the models having minimum values of root mean square error (RMSE), normalized mean square error (NMSE), minimum description length (MDL) and Akaike's information criterion (AIC) and higher values of co-efficient of efficiency (CE) and co-efficient of correlation (r) were considered as best models. Based on the selected criteria, five artificial neural networks based models *i.e.* M-1, M-3, M-5, M-6 and M-7 were found to be performing better than out of the eight models. M-1 model had the minimum values of Akaike's information criterion (-11895.47), minimum description length (-11752.57), normalized mean square error (0.3050), and root mean square error (0.0071 g/l) and maximum values of co-efficient of efficiency (0.9994) and co-efficient of correlation (0.993) in comparison to M-3, M-5, M-6 and M-7 models. Therefore, the performance of the M-1 model was found to be best for prediction of daily suspended sediment concentration at Anandpur station. The order of models performance from best to worst for five selected models was found to be M-1 > M-7 > M-6 > M-5 > M-3.

– It was also found that number of input variables is increasing with discharge in the river.

– On the basis of comparison between qualitative and quantitative evaluation for best model at Anandpur station, the M-1 model in which present day suspended sediment concentration (SSC) depends on the present day discharge and one lag day suspended sediment concentration with (2-7-7-1) network architecture *i.e.* 2 input variables, seven-seven neurons in first and second hidden layers and single output processing element is found to be best out of eight models.

– From the Comparison of M-1 model based on sediment hydrographs for ANN-MLP, MLR and SDR, it was observed that ANN-MLP based sediment hydrograph very closely predicting the peaks accurately out of sediment hydrographs of multiple linear regression analysis and sediment rating curve. It was also observed that sediment hydrograph of multiple linear regression analysis is giving better result than sediment rating curve.

– From the Comparison of M-1 model based on scatter plots for ANN-MLP, MLR and SDR, it was observed on the basis of best fit line and 1:1 line (dotted line) that the SSC are over predicted for smaller values of suspended sediment concentration and under predicted for larger values of suspended sediment concentration for all the methods applied. M-1 model of ANN-MLP nicely demonstrates that most of the data points are quite near the line of best fit in comparison to other methods.

– It was also observed that the results are SRC is very worst to predict the SSC at Anandpur station.

– Therefore, on the basis of qualitative comparison, ANN-MLP was found to be better than other methods for daily suspended sediment concentration prediction at Anandpur station. The values of co-efficient of determination (R^2) for ANN-MLP, MLR and SDR are 0.903, 0.438 and 0.313, respectively, for M-6 model.

– Under quantitative comparison among ANN-MLP, MLR and SDR for M-6 model at Anandpur station, ANN-MLP based M-1 model has the minimum value of root mean square error (0.0071 g/l) and maximum values of co-efficient of efficiency (0.9994) and co-efficient of correlation (0.993). The order of the methods from best to worst at Anandpur station was found to be ANN-MLP > MLR > SDR. Therefore, on the basis of qualitative and quantitative comparison among ANN-MLP, MLR and SDR methods, ANN-MLP was found better than the others for prediction of daily suspended sediment concentration at Anandpur station.

– And finally it was concluded that, artificial neural networks based suspended sediment concentration models can successfully be applied for the prediction of daily suspended sediment concentration at Anandpur station of Baitarani river.

List of abbreviations :

CSSC : Compund suspended sediment concentration
MLR : Multiple linear regression
SRC : Sediment rating curve
SSC : Suspended sediment concentration
OSSC : Observed suspended sediment concentration

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