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Modeling Sediment Runoff : Case Studies from Indian Rivers using ANN Technique

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Abstract : The magnitude of sediments transported by rivers is a major concern for the water resources planning and management. The methods available for sediment estimation are largely empirical, with sediment rating curves being the most widely used. In this study, Artificial Neural Network (ANN) technique has been applied to model the sediment-discharge relationship of two different rivers. Daily data of sediment concentration and discharge of two rivers namely, Satluj River (Indian part and Pranhita River (a sub-basin of Godavari River in India) have been used. A comparison has been made between the results obtained using ANNs and conventional sediment rating curves. The sediment load estimations for the river obtained by ANNs have been found to be significantly superior to the corresponding classical sediment rating curve ones.

INTRODUCTION

The sediment outflow from a catchment is induced by pro-cesses of detachment, transportation and deposition of soil materials by rainfall and runoff. The assessment of the volume of sediments being trans-ported by a river is required in wide spectrum of problems such as the design of reservoirs and dams; hydroelectric power generation and water supply; transport of sediment and pollutants in rivers, lakes and estuaries; determination of the effects of watershed management; and environmental impact assessment

For estimating the sediment concentration/yield, there exist various models and techniques, such as sediment rating curves, erosion modeling, etc. The models vary from a simple regression relationship to complex simulation models. As the sediment-discharge relationship is not linear, conventional statistical tools used in such situations such as regression and curve fitting methods are unable to model the non-linearity in the relationship. On the other hand, the application of physics-based distributed pro-cess computer simulation offers another possible method of sediment prediction. But the application of these complex software programs is often problematic, due to the use of idealized sedimentation components, or the need for massive amounts of detailed spatial and temporal environmental data, which are not available. Simpler approaches are therefore required in the form of 'black-box' modeling tech-niques. Neurocomputing provides one possible an-swer to the problematic task of sediment transfer prediction. In recent years, artificial neural networks (ANNs) which are simplified mathematical representation of the functioning of the human brain, have been widely used in runoff and sediment yield modeling. Three layered feed forward ANNs have been shown to be a powerful tool for input-output mapping and have been widely used in water resources engineering problems (ASCE Task Committee, 2000).

Keeping this in view, in the present study, runoff-sediment modeling has been carried out for two different rivers; one in the north of India and another in the south, namely, Satluj River (Indian part) and Pranhita River (a sub-basin of Godavari River in India) respectively using the ANN technique. A comparison has been made between the results obtained using ANNs and conventional sediment rating curves.

SEDIMENT RATING CURVES

Sediment rating curves are widely used to estimate the sediment concentration being transported by a river. A sed-iment rating curve is a relation between the sediment concentration and river discharge. Sediment rating curves may be plotted showing average sediment concentration or load as a function of discharge averaged over daily, monthly, or other time periods. Rating curves are developed on the premise that a stable relationship between concentration and discharge can be developed which, although exhibiting scatter, will allow the mean sediment yield to be determined on the basis of the discharge history. A problem inherent in the rating curve technique is the high degree of scatter, which may be reduced but not eliminated. Concentration does not necessarily increase as a function of discharge (Ferugson 1986).

Mathematically, a rating curve may be constructed by log-transforming all data and using a linear least square regression to determine the line of best fit. The relationship between load and discharge is of the form:

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

And the log-transformed form will plot as a straight line on log-log paper:

$$\log C = \log a + b \log (Q) \tag{2}$$

Where, C = sediment concentration (or load), Q = discharge, a & b are regression constants.

ARTIFICIAL NEURAL NETWORKS (ANNs)

An ANN is a computing system made up of a highly interconnected set of simple information processing elements, nodes to neutrons, called analogue to neurous in human brain. The neuron collects inputs from both a single and multiple sources and produces output in accordance with a predetermined non-linear function. An ANN model is created by interconnection of many of the neurons in a known configuration. The primary elements characterizing the neural network are the distributed representation of information, local operations and non-linear processing. Fig.1 shows

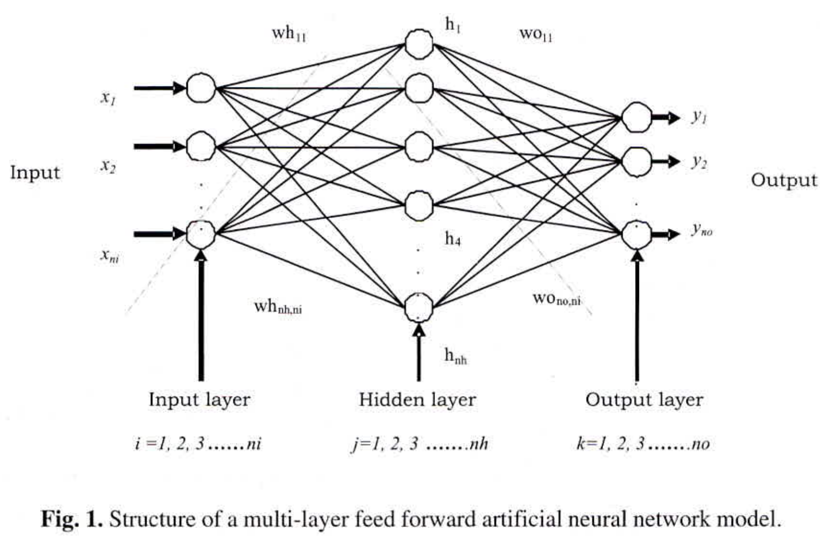


Fig. 1. Structure of a multi-layer feed forward artificial neural network model.

the general structure of a three layer back propagation ANN.

The main principle of neural computing is the decomposition of the input-output relationship into series of linearly separable steps using hidden layers (Haykin, 1994). Generally there are four distinct steps in developing an ANN-based solution. The first step is the data transformation or scaling. The second step is the network architecture definition, where the number of hidden layers, the number of neurons in each layer, and the connectivity between the neurons are set. In the third step, a learning algorithm is used to train the network to respond correctly to a given set of inputs. Lastly, comes the validation or freshing step in which the performance of the trained ANN model is tested through some selected statistical criteria. The theory of ANN has not been described here and can be found in many books such as Haykin (1994).

STUDY AREA, DATA AVAILABILITY AND SELECTION OF INPUT/OUTPUT VARIABLES

Satluj River

The first river chosen for the present study is the Satluj River basin. A part of the whole basin falling in Indian Territory unto Kasol is considered (Figure 2). The Satluj River rises in the lakes of Mansarover and Rakastal in the Tibetan Plateau at an elevation of about 4,572 m and forms one of the main tributaries of Indus River. Indian part of the Satluj basin is elongated in shape. The shape and location of this basin is such that major part of the basin area lies in the greater Himalayas where heavy snowfall is experienced during winters. This large river flows through areas having varying climatic and topographic features. At Namgia, near Shipki, its principal Himalayan tributary, the Spiti joins it, just after entering India. Below this dry region, it flows through the Kinnaur district of

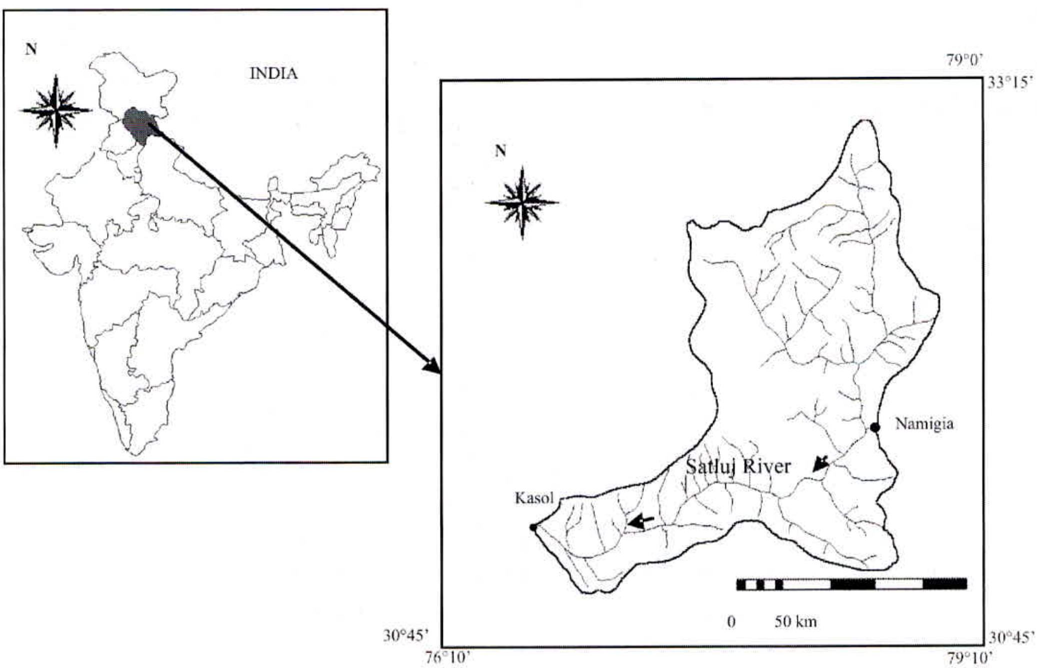


Fig. 2. Map of the Satluj Basin Up to Kasol

Himachal Pradesh, where it gets both snow and rain. Numerous glaciers drain directly into Satluj at various points along its course and many Himalayan glaciers drain into its tributaries. In the lower part of the basin only rainfall is experienced. The total catchment area of Satluj River up to Kasol is about 53,400 km^2, out of which about 19,200 km^2 lies in India including the whole catchment of the Spiti basin that is considered in the study.

The daily data of sediment load and discharge were available at the Kasol site for seven years (1991-97) constituting a total of 2555 patterns. Out of this, 1275 patterns were used for training, 640 patterns for testing and 640 patterns for validation.

Pranhita River

Pranhita River is a major tributary of Godavari River. Pranhita sub-basin system, which conveys the combined waters of Penganga, Wardha and Wainganga, influences the Godavari river system to the maximum possible extent (with 34% drainage area i.e., 1,09,100 km^2 area) by means of rainfall, runoff and sediment transportation. The hydrological data for the study have been collected at Tekra site on Pranhita river (Fig. 3). After the Tekra site, Pranhita river joins the main Godavari in Andhra Pradesh.

The daily data of sediment concentration and discharge were available at the Tekra site for four water years (June 1, 2000 – May 31, 2004) constituting a total of 1461 patterns. Out of this, 730 patterns were used for training, 365 patterns for testing and 366 patterns for validation.

The first step in developing any model is to identify the input and output variables. The output from the models is the sediment concentration at time step t; C_t. It has been shown by many authors that the current sediment concentration can be mapped better by considering, in addition to the current value of discharge, the sediment and discharge at the previous times. Therefore, in addition to Q_t, i.e., discharge at time step t, other variables such as Q_{t-1}, Q_{t-2}, and C_{t-1}, C_{t-2}, were also considered in the input.

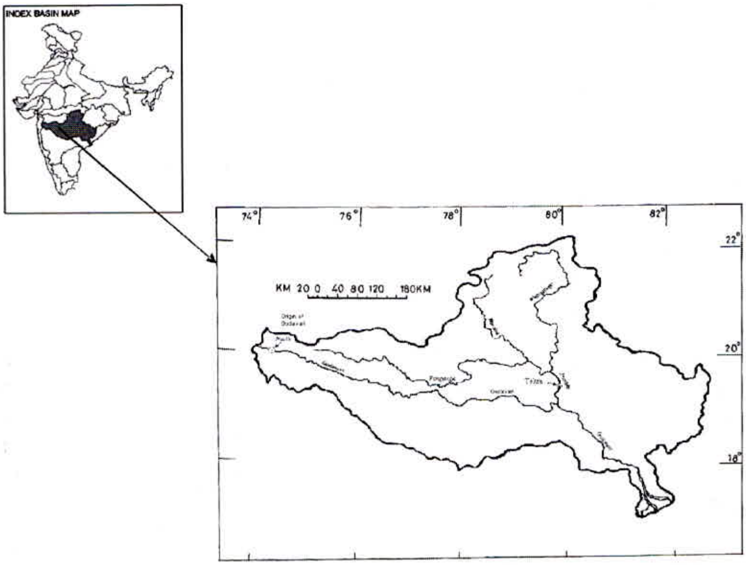


Fig. 3. Pranhita river system and hydrological study location (Tekra site)

DESIGN AND TRAINING OF ANN MODELS

Various combinations of input data considered for training of ANN in the present study are given in Table 1. However, the input-output variables of ANN-1 have been used for the conventional sediment rating curve analysis.

Where, C=Sediment Concentration, Q=Discharge, t represents the time step in days

A back-propagation ANN (BPANN) with the generalized delta rule as the training algorithm has been employed in this study. The ANN package Neural Power (NP), 2003, downloaded from the Internet has been used for the ANN model development. The structure for all simulation models is three and four layer BPANN which utilizes a non-linear sigmoid activation function uniformly between the layers. Nodes in the input layer are equal to number of input variables, nodes in hidden layer are varied from the default value by the NP package for various number of input nodes above to approximately double of input nodes (Zhu et al., 1994) and the nodes in the output layer is one as the models provide single output. According to Hsu et al. (1995), three-layer feed forward ANNs can be used to model real-world functional relationships that may be of unknown or poorly defined form and complexity. Therefore, three-layer networks were tried in this study. However, four layer ANN models were also tried for comparison purpose.

The modeling of ANN initiated with the normalization (re-scaling) of all inputs and output with the maximum value of respective variable reducing the data in the range 0 to 1 to avoid any saturation effect that may be caused by the use of sigmoid function. All interconnecting links between nodes of successive layers were assigned random values called weights. A constant value of 0.15 and 0.8 respectively has been considered for learning rate a and momentum term b selected after hit and trials. The range tried for learning rate a and momentum term b were 0.10-0.40 and 0.7-0.9 respectively. The quick propagation (QP) learning algorithm has been adopted for training of all the ANN models. QP is a heuristic modification of the standard back propagation and is very fast. The network weights were updated after presenting each pattern from the learning data set, rather than once per iteration. The criteria selected to avoid over training was generalization of ANN through cross-validation (Haykin, 1994). For this purpose, the data were divided into training, testing and validation sets. For example, Training data (730 patterns) were used for estimation of weights of the ANN model and testing data (365 patterns) for evaluation of the performance of ANN model during training. Training was stopped when the error for the testing dataset started increasing i.e., when R started decreasing for the testing dataset as the software does not calculate RMSE automatically

Table 1. Various ANN Runoff-Sediment Models

ANN Model	Architecture	Output Variable	Input Variables
ANN-1	[1 – 2 – 1]	C_t	Q_t
ANN-2	[3 – 3 – 1]	C_t	Q_t, Q_{t-1}, C_{t-1}
ANN-3	[5 – 4 – 1]	C_t	Q_t, Q_{t-1}, Q_{t-2}, C_{t-1}, C_{t-2}
ANN-4	[7 – 6 – 1]	C_t	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, C_{t-1}, C_{t-2}, C_{t-3}
ANN-5	[9 – 7 – 1]	C_t	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, Q_{t-4}, C_{t-1}, C_{t-2}, C_{t-3}, C_{t-4}

during testing/validation phase. In this way, the training and testing datasets have been used to assess the performance of various candidate model structures, and thereby choose the best one. The particular ANN model with the best performing parameter values was chosen and the generalized performance of the resulting network has been measured on the validation data set (366 patterns) to which it has never before been exposed. The performance of all the ANN models have been tested through three statistical criterion, viz, root mean square error (RMSE), correlation coefficient (R) and coefficient of determination (DC).

RESULTS AND DISCUSSION

Rating Curve Analysis

Based on the sediment rating curve technique given by equation (1), the sediment rating equation between sediment load and discharge for Satluj River at Kasol site for the training period is

$$C=3E\text{-}08Q^{2.7577} \tag{3}$$

Where, C = Sediment load in the River Satluj at Kasol in tons/Sq.Km at time t

Q = Discharge in the River Satluj at Kasol in Cumec at time t

The sediment rating equation between sediment load and discharge for Pranhita River at Tekra site for the training period is

$$C=(4.94E\text{-}04)Q^{0.770} \tag{4}$$

Where, C = Sediment concentration in the River Pranhia at Tekra in gm/l at time t

Q = Discharge in the River Pranhia at Tekra in Cumec at time t

ANN Modelling

The comparative performance of various ANN models and rating curve analysis in terms of RMSE, R and DC are given in Table 2. It can be seen from Table 2 that the RMSE values are generally low (less than 0.075g/l) for all the ANN models except ANN-1 and ANN-9 models, during training. However, RMSE is lowest for ANN8 (0.151g/l) during testing and for ANN9 (0.162g/l) during validation. Whereas, RMSE of the rating curve model is very high, i.e., 0.472g/l, 0.359g/l and 0.424g/l during training, testing and validation respectively.

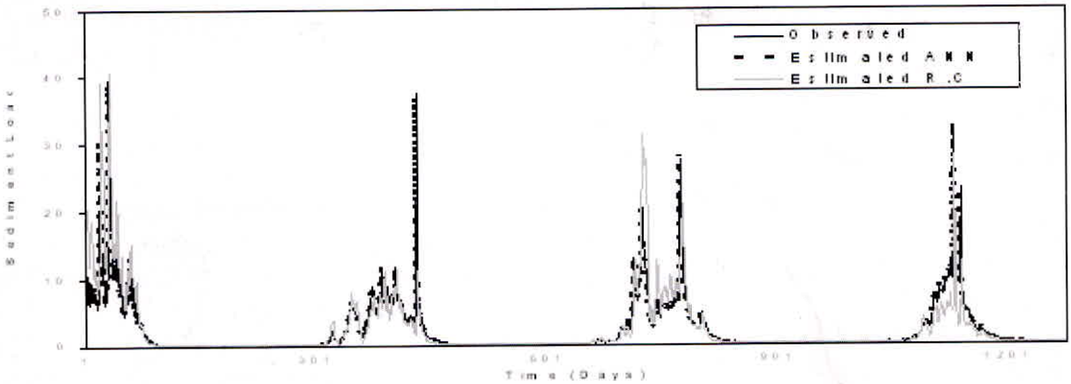
It can be seen from Table 2 that the correlation (R) values are high (more than 0.90) for all the ANN models during all the three phases. The performance of ANN-9 model is the best in R statistic with R values of 0.959 and 0.954 during testing and validation respectively. The performance of the rating curve model is the worst when compared with the ANN models. The R values for rating curve model are 0.923, 0.870 and 0.867 during training, testing and validation respectively. These values are even lower than the worst ANN model, i.e., ANN-1 model.

It can be seen that ANN-2 model and ANN-4 models are the best performing models for Satluj River and Pranhita River respectively. The performance of the rating curve model is average in the R criteria but drastically poor in other two criteria for both the rivers. It is because the estimated sediment series (from sediment rating curve model) follows a good general trend as that of the observed sediment series which gives high R values, but there is a significant difference in the numeric values of observed and estimated sediment concentration due to which the RMSE and DC values are very poor. The performance of the corresponding ANN model with only discharge as input, i.e. ANN-1 is also better as compared with the sediment rating curve technique for both the rivers.

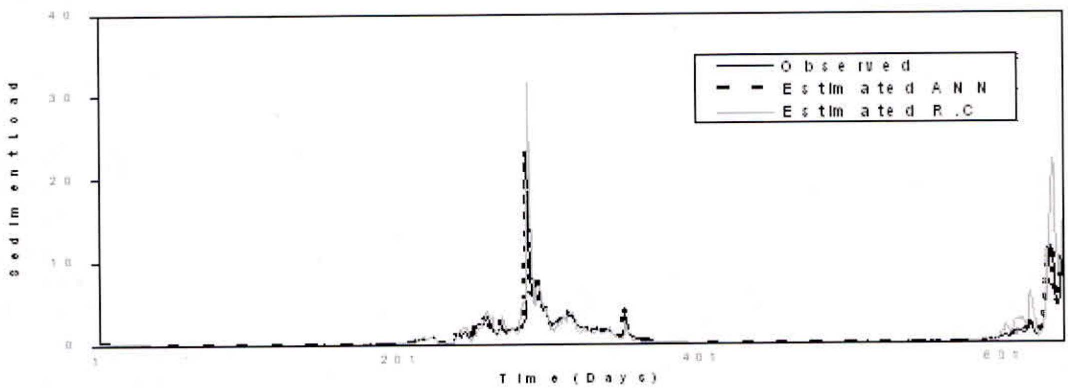
The temporal variation of the observed sediment concentration and the estimate using the conventional technique and ANN for the training, testing as well as validation period for both the rivers is plotted in Figure 4 and Figure 5. It is seen from the graph that ANN estimates very closely

Table 2. Comparative Performance of Various ANN models and Rating Curve

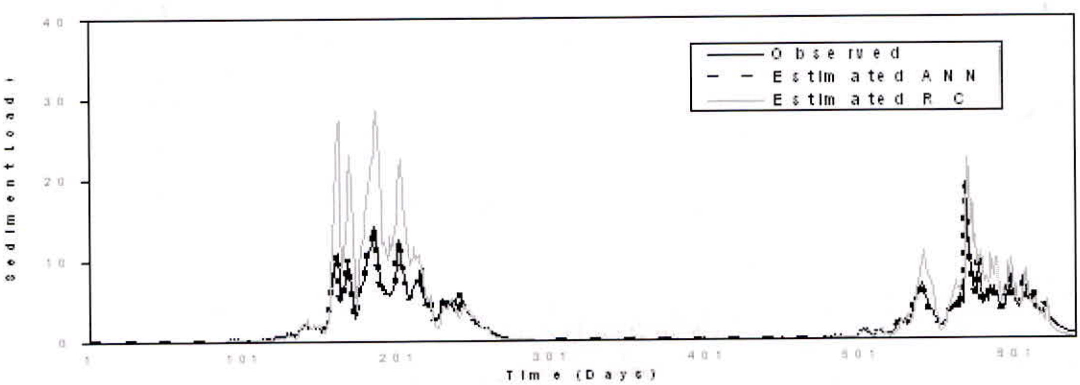
ANN Model	Network Architecture	Training			Testing			Validation		
		RMSE	R	DC	RMSE	R	DC	RMSE	R	DC
SATLUJ RIVER										
ANN1	(1-2-1)	2.000	0.871	0.759	1.040	0.887	0.689	1.510	0.957	0.729
ANN2	**(3-3-1)**	**0.089**	**0.999**	**0.999**	**0.022**	**0.999**	**0.999**	**0.480**	**0.999**	**0.999**
ANN3	(5-4-1)	0.179	0.999	0.998	0.121	0.998	0.996	0.083	0.999	0.999
ANN4	(7-6-1)	0.160	0.999	0.998	0.066	0.999	0.998	0.079	0.999	0.999
ANN5	(9-7-1)	0.258	0.998	0.996	0.111	0.999	0.996	0.013	0.999	0.997
SRC	--	2.560	0.846	0.605	1.398	0.858	0.441	2.780	0.926	0.083
PRANHITA RIVER										
ANN1	[1-2-1]	0.075	0.978	0.957	0.228	0.907	0.743	0.284	0.912	0.667
ANN2	[3-3-1]	0.067	0.983	0.966	0.170	0.951	0.856	0.217	0.946	0.805
ANN3	[5-4-1]	0.063	0.985	0.969	0.174	0.949	0.850	0.223	0.945	0.794
ANN4	**[7-6-1]**	**0.060**	**0.986**	**0.973**	**0.168**	**0.953**	**0.860**	**0.217**	**0.943**	**0.806**
ANN5	[9-7-1]	0.064	0.985	0.969	0.173	0.944	0.852	0.210	0.940	0.819
SRC	--	0.472	0.923	0.680	0.359	0.870	0.870	0.424	0.867	0.668



(a) Training



(b) Testing



(c) Validation

Fig. 3. Comparative performance of observed and estimated sediment Concentration for Satluj River

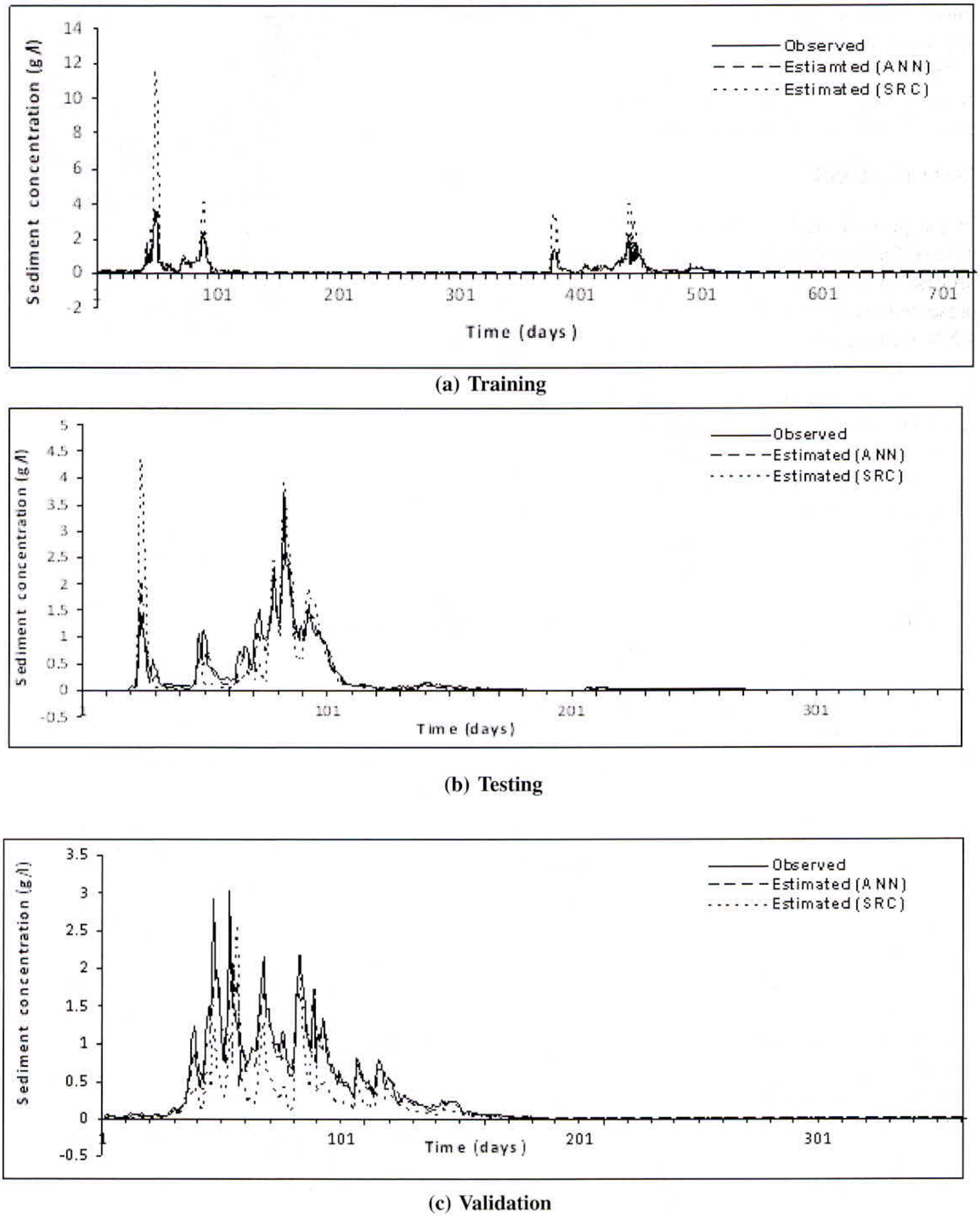


Fig. 4. Comparative performance of observed and sediment concentration series for Pranhita River

follow the observed curve, whereas conventional approach has significant mismatch with the observed curve, especially during the validation phase which conforms to the low coefficient of determination of rating curve technique.

CONCLUSIONS

In the present study ANN technique has been utilized for modeling the sediment load-discharge process in two rivers. The primary aim of the presented study is to illustrate the capability of ANN technique for modeling sediment load in rivers. To achieve the objectives, two case studies have been carried out utilizing daily data of the gauging sites of Satluj river and Pranhita river in India for analysis. The results of ANN have been compared with those of the conventional sediment rating curve approach. ANN results have been found to be much closer to the observed values than the conventional technique.

The study demonstrates that ANN technique can be successfully applied for development of reliable relationships between sediment and discharge in a river when other approaches cannot succeed due to the uncertainty and the stochastic nature of the sediment movement. Moreover, ANN technique has preference over the conventional methods as ANNs can

accept any number of effective variables as input parameters without omission or simplification as commonly done in conventional methods. The presented ANN model is designed by using only field river data, and it has no bound-ary conditions in application. The only restriction is that the model cannot estimate accurately the sediment load for data out of the range of training pattern data. Such a problem can easily be overcome by feeding the training patterns with wide range data.

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