Potential of ANN based Sediment Modelling for Efficient Management of Water Resources

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ABSTRACT:
Assessment of the volume of sediments being transported by a river is required in a wide spectrum of problems such as design of reservoirs and dams; hydroelectric power generation and water supply; water quality and pollution and environmental impact assessment. Therefore, accurate estimate of sediment load by the river is of vital importance for the design and management of water resources projects. There exist various models and techniques for estimating the sediment load such as sediment rating curves, erosion modelling, 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 process computer simulation offers another possible method of sediment prediction. But the application of these complex software programs is often problematic due to the need for massive amounts of detailed spatial and temporal environmental data, which are generally not available. The most widely used conventional sediment rating curves, based on regression equations link the spatial variation in annual sediment yield to climatic and physiographic variables of the basin. However, they are not able to provide sufficiently accurate results. 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 modelling. Three layer feed forward ANNs have been shown to be a powerful tool for input-output mapping and have been widely used in water resources problems. In the present paper, ANN models have been developed for simulation of daily suspended sediment load in three different river basins of India. Single layer feed forward back propagation ANN models have been developed for the three basins namely, Satluj River basin of Western Himalayan region, Subansiri River basin of the Brahmaputra River system from Eastern Himalayan region and Pranhita River basin of the Godavari River system from Southern India. Results obtained indicate that the ANN approach for modelling the complex sediment load simulation produces reasonably satisfactory results for all the three catchments. ANN models were found to be considerably better than the regression models.

1.0 INTRODUCTION

Rigorous assessment of sediment fluxes in rivers is required in a wide spectrum of problems such as design of reservoirs and dams; hydroelectric power generation and water supply; water quality and pollution and environmental impact assessment (Singh *et al*., 1998). Therefore, accurate estimate of sediment flux by the river is of vital importance for the design and management of water resources projects. In the past few decades, great strides have been made in conceptualizing the process of runoff generation and sediment yield/flux from catchments through varying modelling approaches (Flaxman, 1972; Walling, 1983; Wicks and Bathurst, 1996; Van Oost *et al.,* 2000; Verstraeten *et al*., 2003). Models are classified according to their degree of representation of the physical processes involved in abstraction of the real sediment flux phenomenon. They are classified as physically based distributed models, conceptual models, empirical models and black-box models in decreasing degree of representation and increasing degree of application simplicity.

The physically-based distributed models attempt to represent the spatial heterogeneity of variables by dividing the catchment into grids and describe the processes of the sediment transport from grid to grid with simplified partial differential equations (Wicks and Bathurst, 1996). These models can provide satisfactory simulation and prediction for small and heavily instrumented catchments (<100 km^2). However, their applications at regional and larger scales are unrealistic because the quantity and quality of necessary input data are usually insufficient. Lumped conceptual models are favoured in terms of their limited data requirements and inclusion of a conceptual framework. However, lumped conceptual models also require a lengthy calibration and parameterization process. Empirical models estimate suspended sediment flux by relating it to catchment characteristics such as drainage area, topography, land cover and climate (Walling, 1983). They are widely used because of their relatively simple structure and ability to work with limited input data. However, empirical models are unable to represent the spatial variability of hydrologic processes and catchment parameters that influence the suspended sediment flux in a river. Black-box models in the form of regression models can simulate the highly nonlinear suspended sediment flux with limited accuracy, due to their simple model structure and underlying distribution assumptions. In this context, neurocomputing provides one possible answer 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 modelling. Three layer feed forward ANNs have been shown to be a powerful tool for input-output mapping and have been widely used in water resources problems (ASCE Task Committee, 2000).

The application of ANN approach for modelling sediment-discharge process is very recent, and has already produced very encouraging results. In a research project by Rosenbaum (2000), ANN technique has been used to predict sediment distribution in Swedish harbors. Baruah et. al. (2001) developed neural network models of Lake surface chlorophyll and sediment content from LandsatTM imagery in order to assess the water quality of the lake Kasumigaura in Japan and found that back propagation neural network with only one hidden layer could model both the parameters better than conventional regression techniques. Jain (2001) used the ANN approach to establish an integrated stage-discharge-sediment concentration relation for two sites on the Mississipi River and showed that the ANN results were much closer to the observed values than the conventional technique. Nagy et al. (2002) applied ANN technique to estimate the natural sediment discharge in rivers in terms of sediment concentration and addressed the importance of choosing an appropriate neural network structure and providing field data to that network for training purpose. Tayfur (2002) used ANN to simulate experimentally observed sediment fluxes from different slopes under various rainfall intensities. Kisi (2004) used ANN to simulate daily suspended sediment concentration at two stations on the Tongue River in Montana, USA.Tayfur & Guldal (2006) developed a three-layer feed-forward ANN model using a back-propagation algorithm to predict daily total suspended sediment in rivers by testing several cases of different data lengths for the Tennessee basin, in order to obtain an optimal period for training ANNs. Further, it was observed that the ANN model shows better performance than the linear black-box model, based on two-dimensional unit sediment graph theory (2D-UGST). Applying *k*-fold partitioning in the training data set, Cigizoglu & Kisi (2006) showed that superior sediment estimation performance may be obtained with quite limited data, provided that the sub-training data statistics are close to those of whole testing data set. ANN and fuzzy models were found to be considerably better than conventional rating curve method by Lohani et al. (2007).

In the present paper, ANN models have been developed for simulation of daily suspended sediment load in three different river basins of India, namely, Satluj River basin of Western Himalayan region, Subansiri River basin of the Brahmaputra River system from Eastern Himalayan region and Pranhita River basin of the Godavari River system from Southern India. Results obtained indicate that the ANN approach for modelling the complex sediment load simulation produces reasonably satisfactory results for all the three catchments. Conventional sediment rating curves (SRC) have also been developed for the three basins using data similar to ANN and a comparison of these techniques has been made.

2.0 SEDIMENT RATING CURVES

Sediment rating curves are widely used to estimate the sediment load being transported by a river. A sediment rating curve is a relation between the sediment 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 log-log relationship between load and discharge is of the form:

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

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

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

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

3.0 ARTIFICIAL NEURAL NETWORKS (ANNs)

An ANN is a computing system made up of a highly interconnected set of simple information processing elements, analogous to a neuron, called units. 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.

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 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).

4.0 STUDY AREA AND DATA AVAILABILITY

Study basins chosen for the present study are shown in Figure 1.

4.1 Satluj River Basin.

A part of the whole basin falling in Indian Territory unto Kasol is considered 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 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.

4.2 Subansiri River Basin

The Subansiri River is the biggest north bank tributary of river Brahmaputra in India. It originates in Tibet beyond the Great Himalayan Range at an altitude of around 5340 m and joins the Brahmaputra in the plains of Assam State in India. The region of Subansiri basin has three distinct parts that include 1) the great Himalayan range 2) the Sub-Himalayas and 3) fertile plains of Assam. In the mountainous terrain, the river has a total length of about 208 km and falls from 4206 to 80 masl near Dulangmukh in the foothills. As it flows across the central Himalaya to the Arunachal foothills, the Subansiri receives discharge from numerous streams. The total length of known and well-defined tributaries of Subansiri is 1960 km. The Subansiri River contributes about 10.7% of the total discharge of the river Brahmaputra at Pandu near Guwahati in India. The catchment area of Subansiri basin up to the outlet at Chouldhuaghat is approximately 26,419km^2 from SRTM data, of which about 10,237 km^2 (38.75%) lies in Tibet and the remaining 61.25% in India. The daily data of sediment concentration and discharge were available at the Choulduaghat site for ten years (1997-2006) constituting a total of 3652 patterns. Out of this, four years (1997-2002) consisting of 2191 patterns were used for training, two years (2003-2004) consisting of 731 patterns for testing and two years (2005-2006) consisting of 730 patterns for validation.

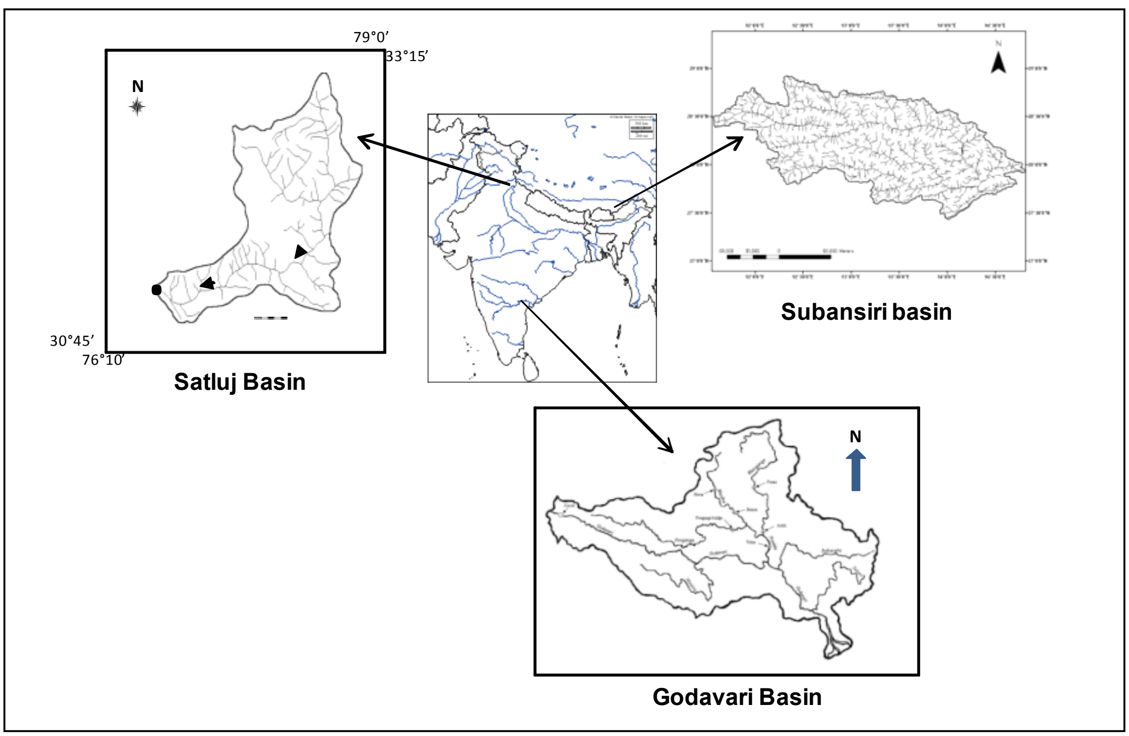


Fig.1: Study Basins

4.3 Pranhita River Basin

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 has been collected at Tekra site on Pranhita River. 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.

5.0 DESIGN AND TRAINING OF ANN MODELS

The first step in developing any model is to identify the input and output variables. The output from the models is the sediment load at time step t; S_t. It has been shown by many authors that the current sediment load 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 S_{t-1}, S_{t-2}, were also considered in the input.

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.

Table 1: Various ANN Runoff-Sediment Models

ANN Model	Output Variable	Input Variables
ANN-1	S_t	Q_t
ANN-2	S_t	Q_t, Q_{t-1}, S_{t-1}
ANN-3	S_t	Q_t, Q_{t-1}, Q_{t-2}, S_{t-1}, S_{t-2}
ANN-4	S_t	Q_t, Q_{t-1}, Q_{t-2}, Q_{t-3}, S_{t-1}, S_{t-2}, S_{t-3}
ANN-5	S_t	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}

Where, S=Suspended sediment concentration at gauging site, Q=Discharge at gauging site, t represents the time step

A back-propagation ANN with the generalized delta rule as the training algorithm has been employed in this study. The ANN package Neural Power (2003) downloaded from the Internet has been used for the ANN model development. The structure for all simulation models is three 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, only three-layer ANN were tried in this study.

The modelling 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 0.5 respectively has been considered for learning rate α and momentum term β selected after hit and trials. The quick propagation (QP) learning algorithm has been adopted for the 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. Training data were used for estimation of weights of the ANN model and testing data for evaluation of the performance of ANN model during training. Training was stopped when the error for the testing dataset started increasing. 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 to which it has never before been exposed. The performance of all the ANN model has been tested through three statistical criterion, viz, root mean square error (RMSE), correlation coefficient (r) and Nash & Sutcliffe coefficient of efficiency, CE (Nash and Sutcliffe, 1970).

6.0 RESULTS AND DISCUSSION

Based on the SRC technique given by equation (1), the sediment rating equation between sediment load and discharge for the three river at at respective gauging sites for the training period are given below:
Satluj River at Kasol

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

Subansiri River at Chouldhuaghat

$$S = 7E\text{-}06\ Q^{1.2923} \tag{4}$$

Pranhita River at Tekra

$$S = 4.94E\text{-}04Q^{0.770} \tag{5}$$

Where, S = Sediment concentration in the River at respective gauging site in g/l at time t
Q = Discharge in the River at respective gauging site in Cumec at time t

The comparative performance of various ANN models and rating curve analysis in terms of RMSE, r and Nash CE are given in Table 2.

It can be seen from Table 2 that the RMSE values are generally low (less than 0.3, 0.04 and 0.07 for Satluj, Subansiri and Pranhita respectively) for all the ANN models except ANN-1 model, during all the three phases, i.e., training, testing as well as validation. It is also seen from the Table 2 that the RMSE values are highest for the rating curve model of all the rivers, even more than the worst ANN model. It is observed from Table 2 that the correlation (r) values are very high (more than 0.95) for all the ANN models except ANN-1 model, during all the three phases. The almost equal values of r during all phases indicate good generalization capability of the ANN model. The performance of the rating curve model are the worst. Again, the r values of SRC are even lower than the worst ANN model, i.e., ANN-1 model. Similary, in the Nash efficiency (CE) statistic, all the ANN models except ANN-1 perform well. The CE values also are very high (more than 0.98) for ANN-2 to ANN-5 during all the three phases. The performance of rating curve model in CE statistic has gone down drastically with CE values as low as -7.55 testing of model in Subansiri basin. These CE values are much lower than the worst ANN model also.

Therefore, ANN-2, ANN-3 & ANN-4 model is the best performing model in all the three statistical and hydrological criteria for simulation of suspended sediment concentration in Satluj, Subansiri and Pranhita respectively. The performance of the rating curve model is average in the r criteria but drastically poor in other two criteria. 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 load due to which the RMSE and r 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.

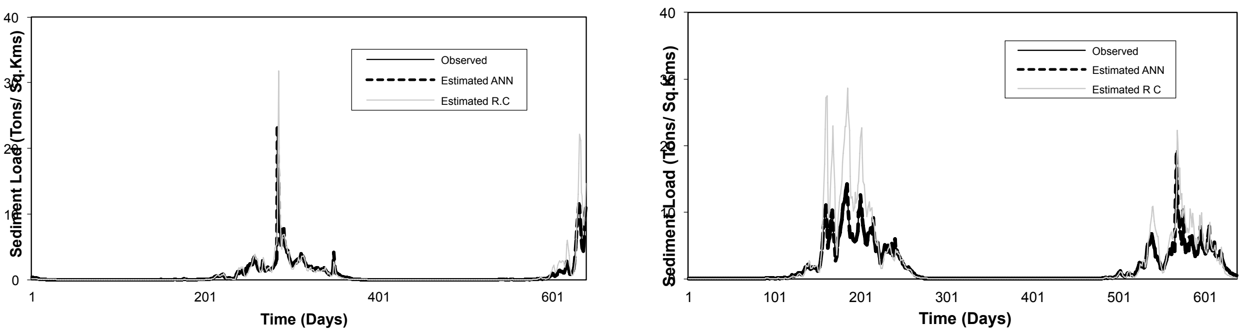
The temporal variation of the observed suspended sediment concentration and the estimated SRC and the best performing ANN for the training, testing as well as validation period for all the three river basins considered in the present study are plotted in Fig 3. It is seen from the graphs that the ANN estimates very closely follow the observed curve, whereas the SRC has significant mismatch with the observed curve, during validation as well as cross-validation phases which conforms to the low Nash efficiency of the rating curve technique.

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

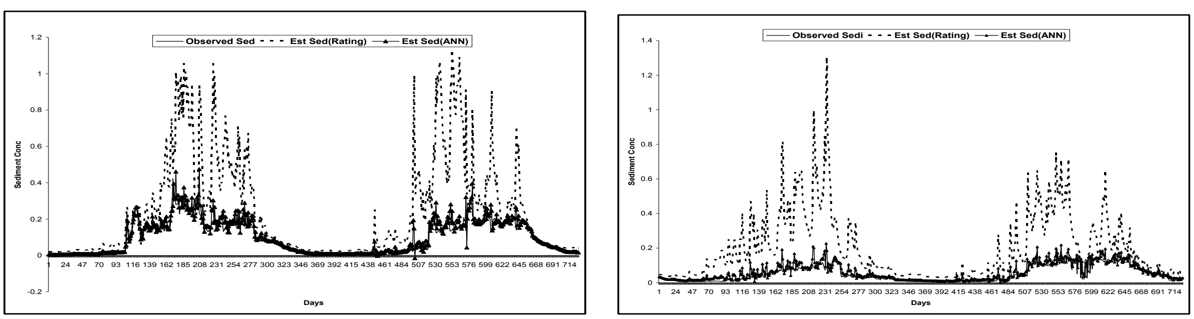
ANN Model (Nodes)	Training			Testing			Validation		
	RMSE (Abs)	r	Nash CE	RMSE (Abs)	r	Nash CE	RMSE (Abs)	r	Nash CE
Satluj River Basin									
ANN-1 (1-2-1)	2.000	0.871	0.759	1.040	0.887	0.689	1.510	0.957	0.729
ANN-2 (3-3-1)	**0.089**	**0.999**	**0.999**	**0.022**	**0.999**	**0.999**	**0.480**	**0.999**	**0.999**
ANN-3 (5-4-1)	0.179	0.999	0.998	0.121	0.998	0.996	0.083	0.999	0.999
ANN-4 (7-6-1)	0.160	0.999	0.998	0.066	0.999	0.998	0.079	0.999	0.999
ANN-5 (9-7-1)	0.258	0.998	0.996	0.111	0.999	0.996	0.013	0.999	0.997
Rating Curve	2.560	0.846	0.605	1.398	0.858	0.441	2.780	0.926	0.083
Subansiri River Basin									
ANN-1 (1-2-1)	0.178	0.878	0.771	0.1519	0.417	0.468	0.1479	0.770	0.628
ANN-2 (3-3-1)	0.037	0.995	0.989	0.0375	0.996	0.991	0.0369	0.995	0.990
ANN-3 (5-4-1)	**0.034**	**0.996**	**0.991**	**0.0344**	**0.995**	**0.990**	**0.0341**	**0.996**	**0.993**
ANN-4 (7-6-1)	0.037	0.995	0.989	0.0335	0.994	0.988	0.0283	0.996	0.990
ANN-5 (9-7-1)	0.034	0.996	0.991	0.0336	0.992	0.983	0.0266	0.995	0.989
Rating Curve	0.199	0.834	0.457	0.2663	0.512	-7.55	0.2182	0.434	-21.3
Pranhita River Basin									
ANN-1 (1-2-1)	0.075	0.978	0.957	0.228	0.907	0.743	0.284	0.912	0.667
ANN-2 (3-3-1)	0.067	0.983	0.966	0.170	0.951	0.856	0.217	0.946	0.805
ANN-3 (5-4-1)	0.063	0.985	0.969	0.174	0.949	0.850	0.223	0.945	0.794
ANN-4 (7-6-1)	**0.060**	**0.986**	**0.973**	**0.168**	**0.953**	**0.860**	**0.217**	**0.943**	**0.806**
ANN-5 (9-7-1)	0.064	0.985	0.969	0.173	0.944	0.852	0.210	0.940	0.819
Rating Curve	0.075	0.978	0.957	0.228	0.907	0.743	0.284	0.912	0.667

CONCLUSIONS

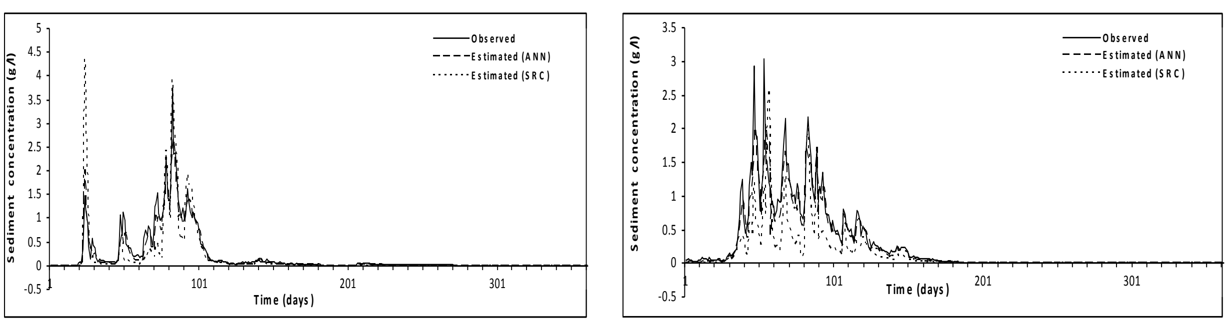
In the presented study ANN technique has been utilized for modeling the sediment-discharge process in three different river basins in India. The primary aim of the presented study is to illustrate the capability of the ANN technique for modeling the sediment load in rivers. To achieve the objectives, case studies have been done utilizing the data of Satluj River at Kasol gauging site Subansiri River at Choulduaghat gauging site and Pranhita River at Tekra gauging site in India for the analysis. The results of ANN have been compared with those of the conventional sediment rating curve (SRC) approach. ANN results have been found to be much closer to the observed values than SRC. The study shows that the ANN technique can be successfully applied for the 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.



(a) Satluj River Basin



(b) Subansiri River Basin



(c) Pranhita River Basin

Figure 4: Comparative Performance of Observed, Estimated (ANN) and Estimated (SRC) Suspended Sediment Concentration Series during validation and cross-validation

Moreover, the 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 the conventional methods. The presented ANN model is designed by using only field river data, and it has no boundary conditions in application. The only restriction is that the model cannot estimate accurately the sediment concentration for data out of the range of the training pattern data. Such a problem can easily be overcome by feeding the training patterns with wide range data. Site engineers can calculate sediment load using the ANN without prior knowledge of the sediment transport theories, provided they know the bounds of the data used to generate the ANN.

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