ISSN: 2278-0181
ETWQQM -2014 Conference Proceedings

Back Propagation Artificial Neural Network Models For Suspended Sediment Simulation – Case Studies From Four Indian Rivers

Archana Sarkar
Scientist 'D'
National Institute of Hydrology
Roorkee-247667. INDIA

***Abstract* -- The magnitude of sediments transported by Rivers is a major concern for the water resources planning. The methods available for sediment estimation are largely empirical, with sediment rating curves being the most widely used, especially in India. In this paper, summary and comparison of four case studies carried out by the author where back propagation artificial neural network (ANN) models have been developed to simulate the suspended sediment load in four Indian rivers namely, Sutlej River of the Indus River system, Kosi River of the Ganges River system, Subansiri River of the Brahmaputra River system and Pranhita River of the Godavari River system. Daily data of sediment load and discharge have been used. A comparison has been made between the results obtained using ANNs and sediment rating curves. The suspended sediment load estimations in all the rivers obtained by ANNs have been found to be significantly superior to the corresponding classical sediment rating curve ones.**

Keywords: Artificial Neural Network; Suspended Sediment; load; Pranhita River; Kosi River; Subansiri River; Sutlej River

I. INTRODUCTION

The sediment outflow from a catchment is induced by processes of detachment, transportation and deposition of soil materials by rainfall and runoff. The assessment of the volume of sediments being transported by a river is required in a 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. The soil erosion and sediment yield is one of the major problems in Himalayan region. The fragile ecosystem of Himalayas has been an increasing cause of concern to environmentalists and water resources planners. The steep slopes in the Himalayas along with depleted forest cover, as well as high seismicity have been major factors in soil erosion and sedimentation in river reaches (Varshney et al., 1986). The rivers emerging out from the Himalayan region transport the sediment at a very high rate. Himalayan and Tibetan region cover only about 5% of the Earth's land surface, but they supply about 25 percent of the dissolved load to the world oceans (Raymo and Ruddiman, 1992). In the Himalayan Mountains, as a consequence of loss of forest cover coupled with the influence of the monsoon pattern of rainfall, the fragile catchments have become prone to low water retention and high soil loss associated with runoff (Rawat and Rawat 1994). Keeping this in view, three Rivers, namely Sutlej, Kosi and Subasiri flow through the different Himalayan regions of India, have been selected for this study. The fourth river, namely Prahita flows through the Southern part of India.

For simulating the suspended sediment load, 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 process 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 'conceptual' solutions or 'black-box' modeling techniques. 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 modeling. 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 modeling 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. An integrated approach incorporating advantages of both deterministic methods and ANNs has been developed by Lin & Namin (2005). The integrated approach has been reported to generate more reliable predictions of suspended sediment transport under practical and complex conditionsA three-layer feed-forward ANN model with back propagation algorithm has been developed by Tayfur & Guldal (2006) for the prediction of daily total suspended sediment load in rivers by testing several cases of different data lengths for the Tennessee basin. Cigizoglu & Kisi (2006) have also showed that superior sediment estimation performance may be obtained with quite limited data by applying k-fold partitioning in the training data set, provided that the sub-training data statistics are close to those of whole testing data set.

In the present study, two techniques, namely, sediment rating curve and back propagation artificial neural networks (ANNs), have been applied for simulating the suspended sediment load in four Indian rivers namely, Sutlej River of the Indus River system, Kosi River of the Ganges River system, Subansiri River of the Brahmaputra River system and Pranhita River of the Godavari River system and a comparison of these techniques has also been made.

II. 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.

III. 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. Fig.1 shows 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.

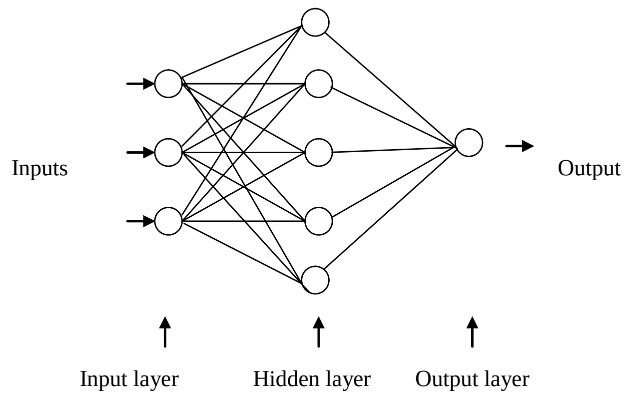

Fig 1. Structure of a multi-layer feed forward artificial neural network model.

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).

IV. STUDY AREA AND DATA AVAILABILITY

Study Rivers chosen for the present study are shown in Figure 2.

A. Sutlej River

A part of the whole basin falling in Indian Territory unto Kasol is considered The Sutlej 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 Sutlej 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 Sutlej 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 Sutlej 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, 1595 patterns were used for training and 960 patterns for testing.

B. Kosi River

Kosi in the state of Bihar in India is a large alluvial river with low gradients and and wide flood plains. Meandering or lateral shifting of alluvial rivers produces cutoff meanders, oxbox lakes and distinctive landforms. Tectonic and environmental changes can cause aggredation and degradation in alluvial rivers and leads to the high soil erosion and meandering. The Kosi River carries mean annual discharge of 1.6* 10^3 m^3/sec, with monsoon discharge 10 times the lean period discharge. The river carries a very high concentration of suspended sediment load during the monsoon months. The normal flood discharge of Kosi usually remains from 1.5 to 2.0 million cusecs. About 75 to 84 percent of the total runoff occurs in the monsoon months of June to October. On an average total sediments are 0.20 percent of the total runoff. About 95 percent silt load comes down the river during the monsoon floods and only 05 percent of the sediments come down in the remaining non-monsoon months. The total runoff during the non-monsoon months, however is on an average about 19 percent of the total annual runoff. For the present study discharge and sediment load data for a period of five years (2000-2004) have been used. However during this period some of the data is missing therefore the data of 1502 days have been considered. This data is available at the Birpur gauging site. There is a barrage at Indo-Nepal border near Birpur. The unit of discharge data available is in cusec while sediment load data is in cubic feet. Out of 1502 data patterns, 951 patterns were used for training and 551 patterns for testing.

C. Subansiri River

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, 2556 patterns were used for training and 1096 patterns for testing.

D. 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 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, 913 patterns were used for training and 548 patterns for testing.

V. DESIGN AND TRAINING OF BACK PROPAGATION 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.

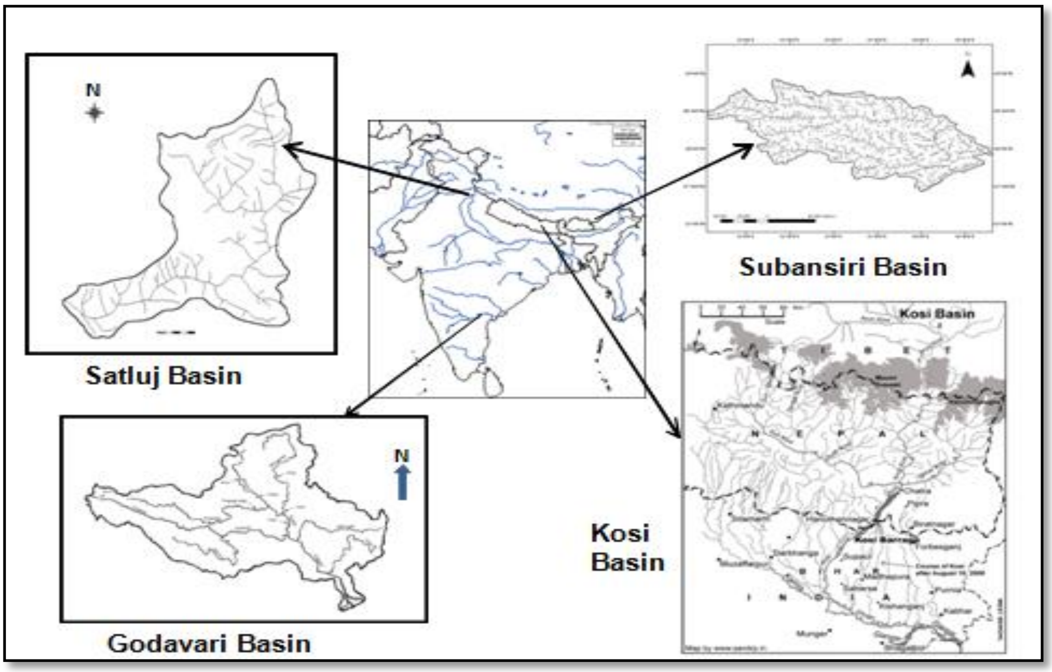

Fig. 2: Study Area

TABLE 1: Various ANN Runoff-Sediment Models

ANN Model	Output Variable	Input Variables
ANN-1	S_t	I. Q_t
II. NN-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=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 networks were tried in this study.

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 0.5 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. 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).

VI. RESULTS AND DISCUSSION

Based on the sediment rating curve 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:

Sutlej River at Kasol

$$S = 3E\text{-}08\, Q^{2.7577} \quad (3)$$

Kosi River at Birpur

$$S = 0.3368 Q^{2.2373} \quad (4)$$

Subansiri River at Chouldhuaghat

$$S = 7E\text{-}06\, Q^{1.2923} \quad (5)$$

Pranhita River at Tekra

$$S = 4.94E\text{-}04 Q^{0.770} \quad (6)$$

Where, S = Sediment concentration in the River at respective gauging site in g/l at time t except for Kosi river at the Birpur site in 10^3cft.

Q = Discharge in the River at respective gauging site in Cumec at time t except for Kosi river at the Birpur site in 10^3cusec.

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 that the RMSE values are generally low for all the rivers for all the ANN models except ANN-1 model, during the two phases, i.e., training and testing. It is also observed 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.

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

ANN Model (Nodes)	Training			Validation		
	RMSE	r	Nash CE	RMSE	r	Nash CE
Sutlej River at Kasol						
ANN-1(1,2,1)	2.000	0.871	0.759	1.510	0.957	0.729
ANN-2 (3,3,1)	0.089	0.999	0.999	0.480	0.999	0.999
ANN-3 (5,4,1)	0.179	0.999	0.998	0.083	0.999	0.999
ANN-4 (7,6,1)	**0.160**	**0.999**	**0.998**	**0.079**	**0.999**	**0.999**
ANN-5 (9,7,1)	0.258	0.998	0.996	0.013	0.999	0.997
Rating Curve	2.560	0.846	0.605	2.780	0.926	0.083
Kosi River at Birpur						
ANN–1 (1,2,1)	4745.0	0.943	0.899	3535.4	0.964	0.926
ANN–2 (3,3,1)	3666.9	0.975	0.944	3067.5	0.977	0.944
ANN–3 (5,4,1)	3001.6	0.987	0.957	3339.9	0.969	0.948
ANN–4 (7,6,1)	**2802.1**	**0.983**	**0.968**	**2965.6**	**0.974**	**0.953**
ANN–5 (9,7,1)	3408.1	0.977	0.944	3619.4	0.969	0.926
Rating Curve	8038.7	0.921	0.852	5252.2	0.951	0.892
Subansiri River at Chouldhuaghat						
ANN-1 (1-2-1)	0.178	0.878	0.771	0.1479	0.996	0.628
ANN-2 (3-3-1)	0.037	0.995	0.989	0.0369	0.770	0.990
ANN-3 (5-4-1)	**0.034**	**0.996**	**0.991**	**0.0341**	**0.996**	**0.993**
ANN-4 (7-6-1)	0.037	0.995	0.989	0.0283	0.996	0.990
ANN-5 (9-7-1)	0.034	0.996	0.991	0.0266	0.995	0.989
Rating Curve	0.199	0.834	0.457	0.2182	0.434	-21.3
Pranhita River at Tekra						
ANN-1 (1-2-1)	0.075	0.978	0.957	0.284	0.912	0.667
ANN-2 (3-3-1)	0.067	0.983	0.966	0.217	0.946	0.805
ANN-3 (5-4-1)	0.063	0.985	0.969	0.223	0.945	0.794
ANN-4 (7-6-1)	**0.060**	**0.986**	**0.973**	**0.217**	**0.943**	**0.806**
ANN-5 (9-7-1)	0.064	0.985	0.969	0.210	0.940	0.819
Rating Curve	0.075	0.978	0.957	0.284	0.912	0.667

It can be seen from Table 2 that the correlation (r) values are very high (more than 0.98) for all the ANN models except ANN-1 model, during both the phases. The performance of ANN-4 model is the best for Sutlej river at Kasol gauging site having input data of previous day discharge and suspended sediment concentration of upto three days. This shows the delayed response of the catchment due to large catchment area. The almost equal values of r and CE during the two phases indicate good generalization capability of the ANN model. Similarly, the performance of ANN-4 model is the best for Kosi river at Birpur gauging site having input data of previous day discharge and suspended sediment concentration of upto three days. However, the performance of ANN-3 model is the best for Subansiri river at Chouldhuaghat gauging site having input data of previous day discharge and suspended sediment concentration of upto two days only. Again, the performance of ANN-4 model is the best for Pranhita river at Tekra gauging site having input data of previous day discharge and suspended sediment concentration of upto three days. The performance of the rating curve model are the worst for all the rivers. These performance indicator values are even lower than the worst ANN model, i.e., ANN-1 model.

Among the four rivers, the performance of ANN model is the best for Sutlej river which is an indication of a stable river (in terms of suspended sediment concentration) and also good quality of observed hydrological data.

VII. Conclusions

In the presented study back propagation ANN technique has been utilized for simulating suspended sediment load in rivers. 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, four case studies has been done utilizing the data at four gauging sites namely Kasol, Birpur, Choudhuaghat and Tekra of the four rivers namely Sutlej, Kosi, Subansiri and Pranhita respectively 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 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.

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.

References

[1] ASCE. Task Committee on Application of Artificial Neural Networks in Hydrology, “Artificial Neural Networks in Hydrology. II: Hydrologic Applications,” Journal of Hydrologic Engineering, ASCE, vol. 5(2), pp 124-137, 2000.

[2] P. J. Baruah, M.Tamura, K. Oki and H. Nishimura, “Neural Network Modeling of Lake Surface Chlorophyll and Sediment Content from LandsatTM Imagery,” Proc. 22nd Asian Conf. on Remote Sensing, 5-9 November 2001, Singapore.

[3] H.K. Cigizoglu and O. Kisi, “Methods to Improve the Neural Network Performance in Suspended Sediment Estimation,” Journal of Hydrology, vol. 317(3-4), pp. 221-238, 2006.

[4] R.I. Ferugson, “River Loads Underestimated by Rating Curves,” Water Resources Research, vol. 22(1), pp. 74-76, 1986.

[5] S.K. Jain, “Development of Integrated Sediment Rating Curves using ANNs,” Journal of Hydraulic Engineering, ASCE, vol. 127(1), pp. 30-37, 2001.

[6] S. Haykin, “Neural Networks - a Comprehensive Foundation,” Macmillan Publishers, New York, 1994.

[7] O. Kisi, (2004) Multi-layer Perceptrons with Levenberg-Marquardt Optimization Algorithm for Suspended Sediment Concentration Prediction and Estimation. Hydrol. Sci. Journal, 49(6), 1025–1040.

[8] B. Lin and M.M. Namin, “Modelling Suspended Sediment Transport Using An Integrated Numerical and ANNs Model,” J. Hydraul. Res., vol. 43(3), pp. 302–310, 2005.

[9] H.M. Nagy, B. Watanabe and M. Hirano, “Prediction of Sediment Load Concentration in Rivers Using Artificial Neural Network Model,” Journal of Hydraulic Engineering, ASCE, vol. 128(6), pp. 588-595, 2002.

[10] J.E, Nash and J.V. Sutcliffe, “River Flow Forecasting through Conceptual Models,” Journal of Hydrology, vol. 10, pp. 282-290, 1970.

[11] Neural Power, “Neural Networks Professional Version 2.0. CPC-X Software, Copyright: 1997-2003,” A Demo version downloaded from the Internet, 2003.

[12] J.S Rawat and M.S. Rawat, “Accelerated Erosion & Denudation in the Nana Kosi Watershed, Central Himalaya, India, Part I: Sediment Load,” Journal of Mountain Research and Development, vol. 14(1), pp. 25-38, 1994.

[13] M.E. Raymo and W.F. Ruddiman, “Tectonic Forcing of Late Cainozoic Climate,” Nature, vol. 359, pp. 117-122, 1992.

[14] M. Rosenbaum, “Harbours- Silting and Environmental Sedimentology (H-SENSE. Final Report,” Dept. of Civil & Structural Engineering, The Nottingham Trent University, Nottingham, UK. http://hjs.geol.uib.no/HSense/, 2000.

[15] De. E. Rumelhart, G. E. Hinton and R. J. Williams, “Learning Representation by Back Propagating Errors,” Nature, vol. 323(9), pp. 533-536, 1986.

[16] G. Tayfur, “Artificial Neural Networks for Sheet Sediment Transport,” Hyrol. Sci. J., vol. 47 (6), pp. 879–892, 2002.

[17] G. Tayfur and V. Guldal, “Artificial Neural Networks for Estimating Daily total Suspended Sediment in Natural Streams,” Nordic Hydrol., vol. 37 (1), pp. 69–79, 2006.

[18] R.S. Varshney, S. Prakash and C.P. Sharma, “Variation of Sediment Rate of Reservoirs in Himalayan Region with Catchment,” Proc. of 53rd R & D Session, CBIP Bubhaneshwar, India, Technical session IX paper, 1986.

[19] M. Fujita and N. Hashimoto, “Application of Neural Networks to Runoff Prediction,” In Stochastic and Statistical Method in Hydrology and Environmental Engineering, vol. 3, K.W. Hipel et al. (Editors)., Kluwer Publishers, The Netherlands, 205-216, 1994.