

Optimal Artificial Neural Network Modeling of Sedimentation yield and Runoff in high flow season of Indus River at Besham Qila for Terbela Dam

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Abstract: *The objective of the study is to develop the relation between sedimentation and discharge of Indus river near to Besham Qila in high flow season because the most of the sedimentation arises in the Indus river in high flow season. In the present study the high flow months are from May to September. The artificial neural network model was used to develop the relation between sedimentation and discharge by changing the different numbers of neurons in hidden layer. The six models A, B, C, D, E, F are performed to develop the relation between sedimentation and discharge but the model C is best fitted model because it gives high correlation with respect to other models and in the last the regression model is developed between sedimentation and discharge. The predicted model can be used as a decision making for hydrologist and engineers and it can also be used to forecast the storage capacity of Tarbela Dam*

Keywords: artificial neural network; ppm; stream flow; forecasting;

1. Introduction

The sediment outflow from the watershed 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; transport of sediment and pollutants in rivers, lakes and estuaries; design of stable channels, dams and debris basins; undertaking cleanup following floods. Artificial neural network (ANN) is a technique with flexible mathematical structure which is capable of identifying complex non-linear relationship between input and output data without detailed the nature of the internal structure of the physical process. The ANN is capable to model any arbitrarily complex nonlinear process that relates sediments load to continuous water discharge. ANN can be employed also to analyze the hysteretic phenomenon of sediment transport. It is a very practical and promising modeling tool in the context of sediment load prediction and its outputs can be potentially used for design and management purposes in water-related development projects. Archana Sarkar et al [1] applied ANN to model the sediment discharge relationship of an alluvial river. Daily data of sediment load and discharge of the Kosi River in India have been used. A comparison has been made between the results obtained using ANNs and sediment rating curves.

Sokchhay Heng et al [4] attempts to combine SSA (singular spectrum analysis) with ANN, called SSA-ANN model, to improve the accuracy of sediment load predicted by the existing ANN approach. In combining with ANN, he proposed SSA-ANN for better performance. YU-Min Wang [5] used artificial neural networks (ANNs) for modeling the event-based suspended sediments concentration (SSC) in Jiasian diversion weir in southern Taiwan. His results showed that the performance of back propagation was slightly better than

GRNN model. In addition, the classical regression performance was inferior to ANNs.

2. Study Area

Tarbela Dam is made on the Indus River to produce electric power and irrigate the land. Its storage is 6.625 MAF (million acre feet). Its inflow is due to rainfall in the catchment which lies in the upstream and because of snowmelt. Rain causes flood in the catchment. The maximum water level in the dam is 1550 ft. Location of Tarbela is about 100 km North West of Islamabad. It is main reservoir which is built for the production of electric power and irrigates the catchment area which is about 4000 sq. miles. It also controls the flood condition.



Figure1: Study Area

The catchment area of Indus river at Tarbela dam is about 168,000 km² and surface area is about 250 km². Annual inflow of Tarbela is 74 BCM in dry year and 79 BCM in wet

year. Geographical Information of Tarbela dam is latitude is 34° 00' 02" N and longitude is 72° 38' 15" E.

3. Materials and Methods

A three-layer neural network with back-propagation algorithm was applied to study the relation of a stream flow and sediment for the Indus River at Besham Qila. Statistica 8.0 was used in this study. Weekly time series of stream flow data of discharge and sediments (1990–2010) were used in order to study the relation between sediments and discharge.

3.1 Artificial Neural Networks (ANN)

An ANN is composed of a set of nodes and a number of interconnected processing elements. ANNs use learning algorithms to model knowledge and save this knowledge in weighted connections mimicking the function of a human brain. The nodes generally have three layers input nodes, hidden nodes and an output node. The first technique of neural network modeling is the MLP model. The MLP is the most commonly used neural computing technique. The architecture of a typical neuron is shown in Figure. output node.

3.2 Multilayer Perception (MLP)

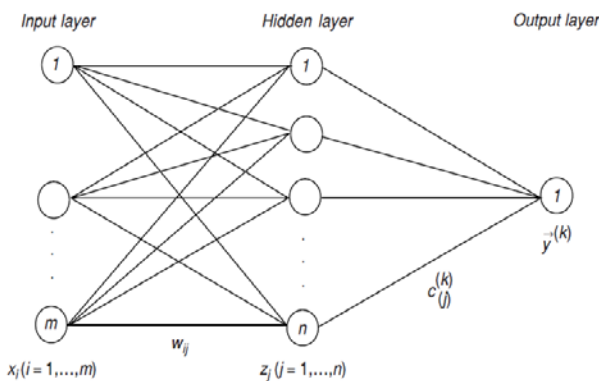


Figure2: ANN model structure

Basically the MLP consists of three layers: the input layer, where the data are introduced to the network; the hidden layer, where the data are processed and the output layer, where the results for given inputs are produced. Each layer is made up of several nodes, and layers are interconnected by sets of correlation weights. Each input node unit ($i = 1, m$) in input layer broadcasts the input signal to the hidden layer. Each hidden node ($j = 1, n$) sums its weighted input signals according to

$$z_{in_j} = w_{0j} + \sum_{i=1}^m x_i w_{ij}$$

applies its activation function to compute its output signal from the input data as

$$z_j = f(z_{in_j})$$

The sigmoid activation function will process the signal that passes from each node by

$$f(z_{in_j}) = \frac{1}{1 + e^{-z_{in_j}}}$$

Then, from the second layer, the signal is transmitted to the third layer. The output unit ($k = 1$) sums its weighted input signals as

$$x_{in_k} = c_0^{(k)} + \sum_{j=1}^n z_j c_j^{(k)}$$

And applies its activation function to compute its output signal,

$$y^{(k)} = f(x_{in_k})$$

Where $c_j^{(k)}$ the weight between the second layer and the third is layer, and $c_0^{(k)}$ is the weight for the bias. The output node ($k = 1$) receives a target pattern corresponding to the input training pattern, computes its error information calculates its weight correction (used to update $c_j^{(k)}$ later), and its bias correction (used to update $c_0^{(k)}$ later) term.

3.3 Processing of Data

The output of the Logistic Activation Function (LAF), which was used in this study, lies in the interval [0,1]; for this reason the original data need to be transformed to the interval [0.05,0.95] before being presented to the network. Each input and output values were normalized with their own specific normalization factors as follows: suppose a and A are the minimum and maximum values of the data series, respectively, then an actual flow value of Q_t was transformed to the interval [0.05,0.95] using the formula:

$$Q_t = \frac{0.90(Q_t - a)}{A - a} + 0.05$$

Where, Q_t = actual value; a = minimum value of Q_t ; A = maximum value of Q_t . After the best network was found, all the transformed data were retransformed back to their original range by the equation:

$$Q_t = \frac{(A - a)(Q_t - 0.05)}{0.9} + a$$

3.4 Training Testing and Validation

The practice adopted in the training and testing was to divide the available data into two independent sets using split sampling tool in the Statistica 8.0 software. The first data set was used for training and the second data set, which is normally about one fourth of the total available data, was used for testing. A one year data was set aside for validating the ANN model. During the training, the learning parameters such as Eta (η), Alpha (α), weight noise, and temperature were set to their default values of 0.2, 0.5, 0, and 1, respectively.

3.5 Model Performance

Accuracy of models can be evaluated by plotting line graphs that show the actual data versus the values predicted by the models. However, the five more formal quantitative measures of accuracy of time series modelling techniques include: the mean absolute error (MAE) and the mean square error (MSE) and correlation between observe and predicted value. These indices measure the differences between the actual values in the time series and the predicted, or fitted, values generated by the model.

4. Results

The Six neural network are used to develop the relation of sediments with discharge of Indus river near to Besham Qila . The statistical analysis of all the models given in table 1

Table 1: The statistical analysis of all the models

Layer structure	MODEL	S.D Error	Corr elation	Train Error	Test Error
MLP 1-1-1	A	1304.3	0.521	0.0047	0.002585
MLP 1-2-1	B	1308.2	0.545	0.0045	0.002591
MLP 1-5-1	C	1313.7	0.570	0.0043	0.002513
MLP 1-10-1	D	1376.3	0.524	0.0048	0.002636
MLP 1-15-1	E	1309.1	0.521	0.0047	0.002640
MLP 1-30-1	F	1315.4	0.511	0.0047	0.002636

The number of neuron in hidden layer was selected by trial and error method . The statistical analysis of each model shows that the neural network model C is best for the relation of sediment and discharge relation because there is very least training error, test error and validation error which is shown in figure 3. The best model for sediment and discharge analysis was selected on the base of correlation therefore the model C shows high correlation amongs all model shown in figure3.

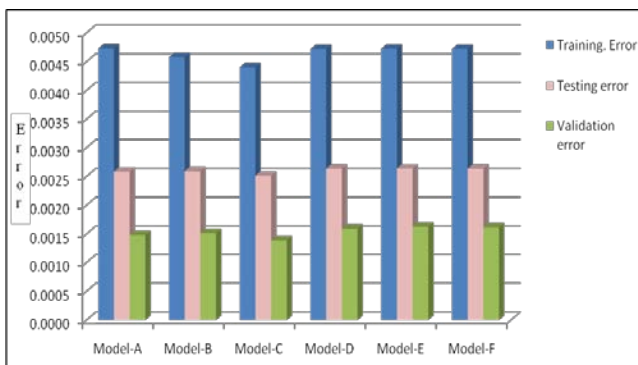


Figure 3: Errors of model

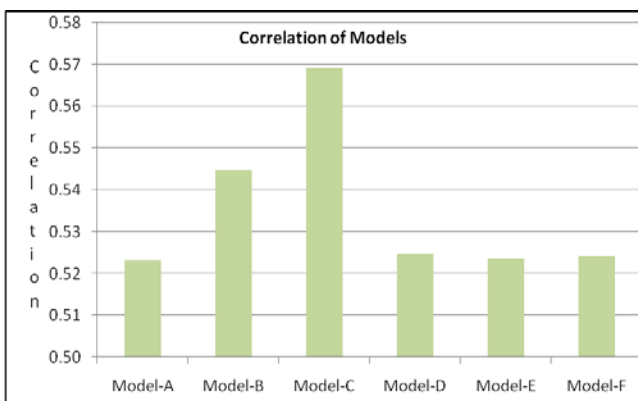


Figure 4: The correlation of each model

The correlation of 0.56 is found in observed and computed sediments for model -C. The performance of each model with respect to observe and computed sediments is shows in the figure 5. The compersion of observe and computed sediments shows that the neural model C have high correlation amongs all neural model . The observe and computed sediments from model C is shown in figure .The figure shows that predicted and observe sediments from model C is very close .

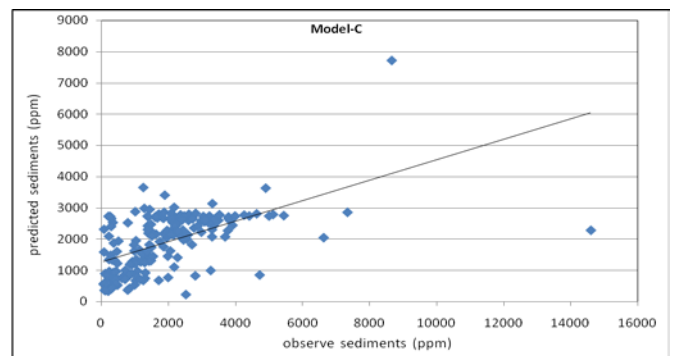
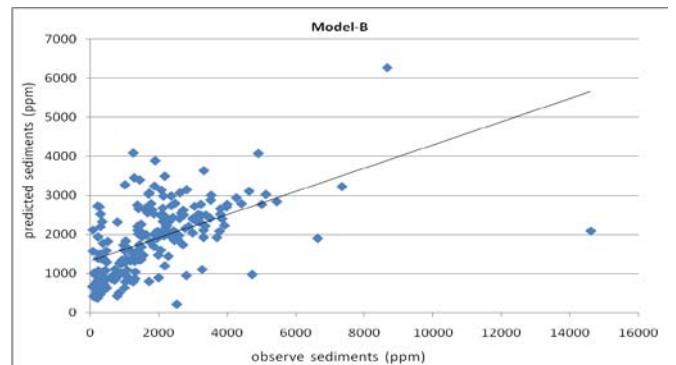
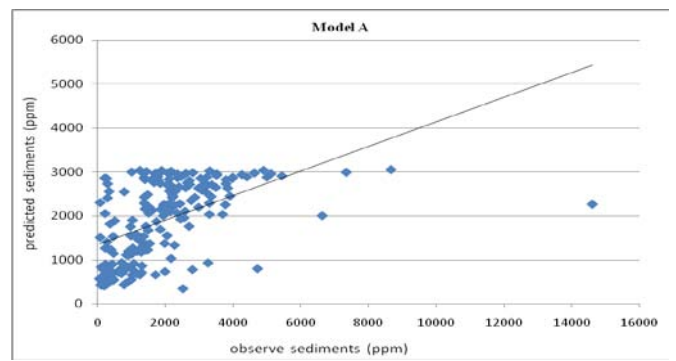
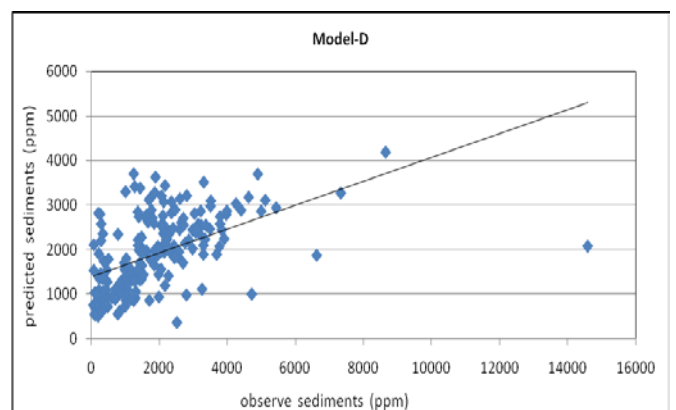


Figure5:(conti)



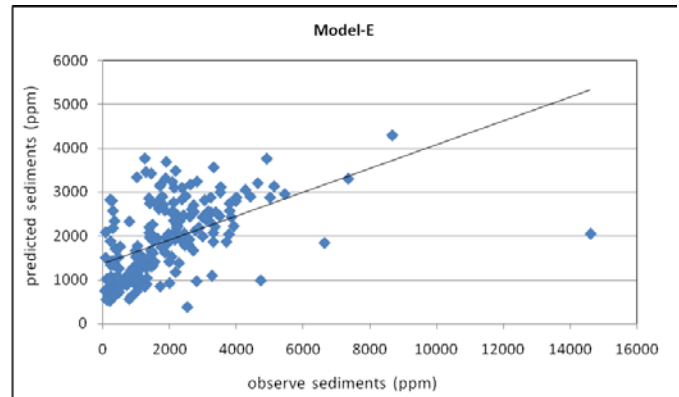
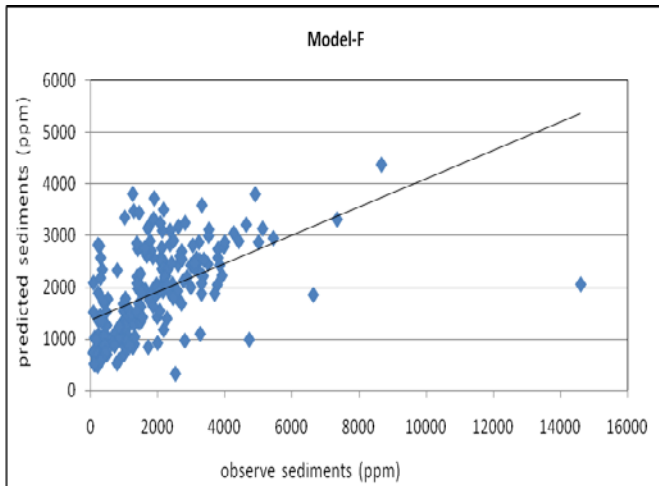


Figure 5: Performance of models

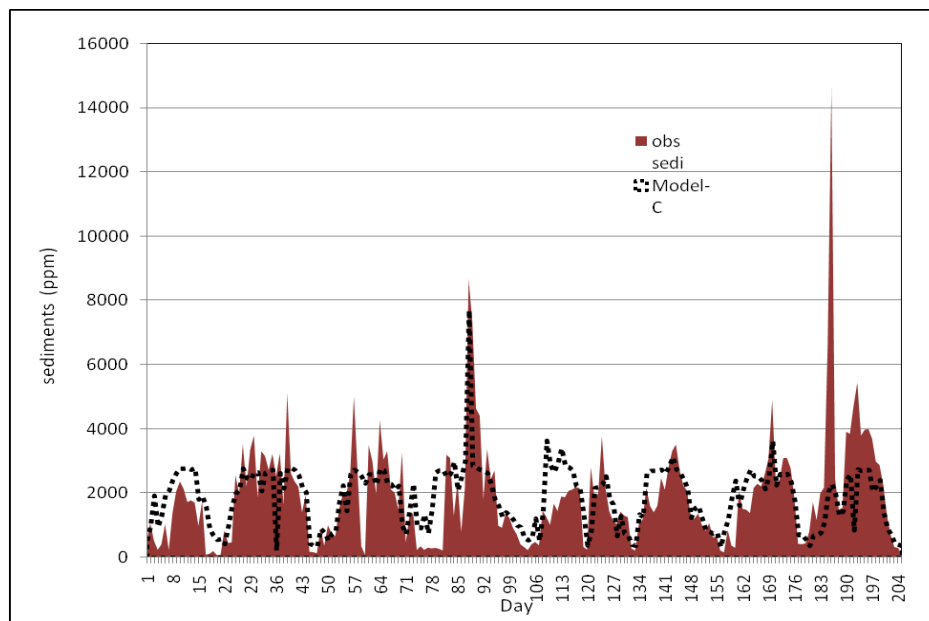


Figure 6: Observe and Computed sediments

5. Conclusions and Recommendations

The information provided by Besham Qila, a gauging station upstream the reservoir, about water discharges and sediment concentrations and the information obtained from the artificial neural network is fundamental to understand the sedimentation processes in the Tarbela Reservoir.

Field data is also extremely useful to validate numerical models. It should be noted that monitoring of sediment related processes is a demanding task, often associated with a certain degree of uncertainty due to high spatial and temporal variability.

The application of a numerical model to simulate sedimentation in the future needs to consider of a series of water discharges and operation levels representative of the future scenario. The results will depend on the assumptions made about the temporal series.

Short term predictions will depend in part on how close the real sequences are to the one used as input in the numerical model. It is assumed that predictions for dates 10 years or

more into the future are representative provided that there is no change in the long term average inflows of water and sediment and the reservoir is operated in the same manner as the model assumes.

Sedimentation deposition is also depends upon rainfall and temperature of the catchment. Neural network can also be developing by using radial base function and forward propagation. It is recommended that more gauging station should be installed to avoid missing and erroneous data and stream flow gages and precipitation stations should be calibrated periodically. The predicted model can be used as a decision making for hydrologist and engineers and it can also be used to forecast the storage capacity of Tarbela Dam.

References

- [1] Archana Sarkar et al "ARTIFICIAL NEURAL NETWORK MODELS FOR ESTIMATION OF SEDIMENT LOAD IN AN ALLUVIAL RIVER IN INDIA" journal of Environmental Hydrology volume 16, 2008, paper 30.

- [2] M. R. Mustafa et al, "Artificial Neural Networks Modeling in Water Resources Engineering: Infrastructure and Applications" World Academy of Science, Engineering and Technology Vol:6 2012 PP 02-24.
- [3] Shailesh Kumar Singh et al "Training of Artificial Neural Networks Using Information-Rich Data" journal of hydrology issue 1, 2014, pp 40-62.
- [4] Sokchhay Heng and Tadashi Suetsugi, "Coupling Singular Spectrum Analysis with Artificial Neural Network to Improve Accuracy of Sediment Load Prediction," Journal of Water Resource and Protection, 2013, issue 5, pp.395-404.
- [5] YU-MIN Wang et al "Using Artificial Neural Networks for Modeling Suspended Sediment Concentration" 10th WSEAS international Conference on mathematical methods and computational techniques in electrical engineering (MMACTEE'08), sofia, Bulgaria, May 2008 , pp 2-4.
- [6] Z A Boukhrissa et al " Prediction of sediment load by sediment rating curve and neural network (ANN) in El Kebir catchment Algeria. J. Earth Syst. Sci. 122, No. 5, October 2013, pp. 1303–1312.

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