Estimation of Sediment Yield for Dasu Hydropower Project Using Artificial Neural Networks

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Abstract

Reservoir sedimentation of Dasu Hydropower Project (DHP) was analysed by developing three ANN architectures of data driven method. The inputs of the ANN model were daily data of the river inflow into the reservoir, river outflow from the reservoir and change in reservoir storage capacity, while the output of the model was the daily amount of sediment retention in the reservoir ponding area. For ANN model inputs, hydrological data of forty years were used in this study (70 % for training, 15 % for validation, and remaining 15 % for testing). The target of the model was estimated by using the HEC-RAS 1-D numerical model. The ANN architectures were created with the multilayer perceptron (MLP) using Marquardt Levenberg training method. In well performed ANN architectures, the transfer function in the hidden layers was 'logsig', while 'purelin' was used as transfer function in the output layer. Among well performed ANN architectures, ANN (4-14-1) performed well in the three layers neural network, ANN (4-8-10-1) performed well in the four layers neural network architecture while ANN (4-5-4-5-1) performed well in the five layers neural network architecture. The results showed that the ANN models selected captured the process of reservoir sedimentation very well in both ways, daily volume of sediment deposition and daily volume of sediment venting out of the reservoir during wettest and driest hydrological cycles. The results also showed that with an increase the length of data set of shorter intervals, the efficiency of the model can be improved. It was also noticed that the length of artificial neural network did not affect the statistical performance of the model when employing short-interval observational data of long period. It was concluded that the artificial neural network is a good tool for the estimation of reservoir sedimentation in the Dasu Hydropower Project.

1. Introduction

The challenge of reservoir sedimentation is depleting per capita availability of water in Pakistan. That is not only affecting agriculture crop water requirement only but also power generation, which it's already facing severe crisis. Per capita water availability in Pakistan has decreased from 5,000 in 1951 to 1100 cubic meter per annum in 2006. The increasing gap between water supply and demand has led to severe water shortage, in almost all sectors, (Martin et al. 2006). The present facts are just above the level of 1,000 m^3 per capita per annum (Falkenmark 1989), the internationally recognized water scarcity rate. In Pakistan, water shortfall between requirement and availability will be 12% in 2025 (Ministery of Water and Power Pakistan 2003). At the moment, the country has only 30 days water storage capacity (Ministery of Water and Power Pakistan 2004). Around 92% of the country's area is classified as semi-arid to arid, facing extreme shortage of precipitation (Food and Agriculture Orgnization of the United Nations 2011). Under this scenario, the construction of mega multi-purpose storage dams is assuming highest priority to sustain irrigated agriculture which is the backbone of Pakistan's economy and to meet the growing power need of the country (Chaudhary et al. 2013).

Prediction of sedimentation is not an easy task due to its high complexity and non-linearity. In recent past, the artificial neural network (ANN) technique, is gaining popularity among the

hydrologic community due to its ability to identify a relationship from given patterns to solve large scale complex problems such as pattern recognition, non-linear modelling and classification (ASCE 2000; ASCE 2000). ANN provided many promising results in the field of hydraulic and civil engineering. For example its working style like human nervous system, to learn from data samples presented, proved it a highly tolerated against data simple errors (Bui et al. 2014). Compared to regression analysis with conventional stochastic dynamic programming, ANN showed superiority to tackle the nonlinearity problems as well as superior simulation model in deriving the operating policy for reservoir systems (Fayaed et al. 2015). (Boukhrissa et al. 2013) made a comparison between suspended sediment rating curves and artificial neural network (ANN) for El Kebir catchment in Algeria. Daily water discharge and daily suspended sediment data from the gauging station of Ain Assel were used as input and output parameter. The model was based on the cascade-forward and feed- forward back propagation using Levenberg-Marquardt and Bayesian regulation algorithms. It was found that ANN model efficiency to produce the daily sediment load and global annual sediment yield was the highest. (Jothiprakash et al. 2009) developed an artificial neural network (ANN) for reservoir sedimentation of Gobindsagar Reservoir at Bhakra Dam on Satluj River in India which is a tributary of Indus River Basin System. In the model, 32 years data of annual rainfall, annual inflow and annual capacity were used as input parameters. The pattern of sediment retained in the reservoir was well captured by the multi-layer perceptron (3-5-1) ANN model using back propagation algorithm with sigmoidal activation function. It was found that ANN estimated the reservoir sedimentation with better accuracy compared to conventional methods. (Rahim and Akif 2015) developed an artificial neural network to study the relationship between sediment yield and Indus river runoff during high flows for Tarbela Dam utilizing Besham Qila's gauge station data. In the three layers neural network with back propagation algorithm, weekly time series data of discharge and sediment load of 20 years was used as an input and output parameter, respectively. The correlation of 0.56 was found in observed and computed sediments for the ANN model. ANN model is also a very efficient tool for water level prediction especially when the duration of quick response components of individual events is less than 6 hours (Rezaeianzadeh et al. 2015).

In the present study, an ANN model has been developed by using 40 years hydrological data for the estimation of sediment load at the under constructed Dasu Hydropower Project. The input parameters such as river discharge into the reservoir, outflows from reservoir and reservoir capacity were decided on the basis of their influence in sedimentation process and sediment load retained in the dam ponding area was considered as the output parameter.

2. Study Area and Methodology

Dasu dam is a gravity dam currently being constructed on the Indus River near Dasu town in Khyber Pakhtunkhwa province of Pakistan (Fig. 1). Its design discharge is of 2,670 m^3/s (Dasu Hydropower Consultants 2013) and one of the series of hydropower development projects included in the vision programme developed by Water and Power Development Authority of Pakistan. In feasibility studies of Dasu HPP, it was decided to construct after completion of an upstream Diamer Bhasha reservoir to provide regulated flows for energy generation and also to control downstream proposed projects reservoir sedimentation (Consultants 2009). Later, a detailed design of the project was conducted without considering any upstream reservoir which will definitely cause huge sedimentation within Dasu reservoir storage area and may be a danger for dam components (Rehman et al. 2015). Catchment area of Indus River at the damsite is 158,800 km^2. Mean annual runoff at dam site is 2,116 m^3/s with lowest river flow of

291 m^3/s. Annual flow volume at Dasu dam site is 66.7 bm^3, 90% of these flows are generated from melting snow and glaciers. Hence nearly 80% of flows occur in summer months from June to September while from October to May is known as the low flow season. Gross storage capacity of reservoir at elevation of 950 masl is about 1.41 bm^3 and operational storage capacity is 0.82 bm^3. (Dasu Hydropower Consultants 2013). The project is going to be constructed with the help of World Bank funding and will operate under Water and Power Development Authority (WAPDA) Pakistan (Dasu Hydropower Consultants 2013). WAPDA is also controlling authority of Pakistan reservoirs, conduct reservoir thalweg surveys regularly to measure actual sediment deposited in the reservoirs. The Indus River originates from Tibetan plateau, to the North of Manasarowar Lake, at an elevation of about 5,500 masl. Operational Mete-Hydrological data stations along Indus River till Dasu site and nearby downstream are at Partab Bridge, Dasu Bridge, Kandia Bridge, Pattan, and Besham Qila.

2.1 Method

The ANN model developed by using simple mass balance equation for the estimation of sediment retained within the reservoir area;

$$\Delta s = q_{w(in)} - q_{w(out)} + q_{s(in)} - q_{s(out)} \quad (1)$$

$$\Delta s = q_{w(in)} - q_{w(out)} + q_{s(R)} \quad (2)$$

$$q_{s(R)} = \Delta s + q_{w(out)} - q_{w(in)} \quad (3)$$

$$\Delta s = s_t - s_{t-1} \quad (4)$$

where,

Δs = change in reservoir capacity (m^3)
$q_{w(in)}$ = water inflow into reservoir (m^3)
$q_{w(out)}$ = water outflow from reservoir (m^3)
$q_{s(in)}$ = sediment incoming in reservoir (m^3)
$q_{s(out)}$ = sediment outgoing from reservoir (m^3)
$q_{s(R)}$ = sediment retained in the reservoir (m^3)

Fig. 1 Location map of the study area, Dasu Hydropower Project on Indus River, Pakistan (Dasu Hydropower Consultants, 2013)

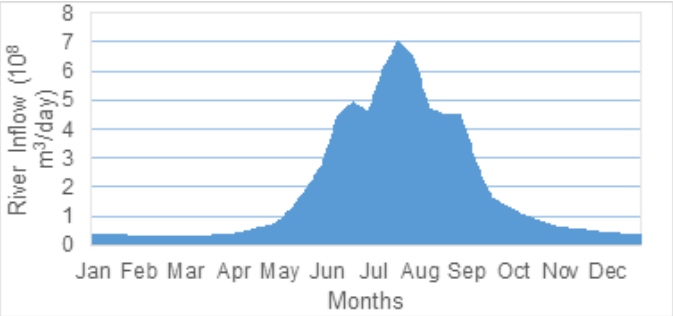

Fig. 2 ANN input, daily inflow hydrograph of moderate hydrological year (1999)

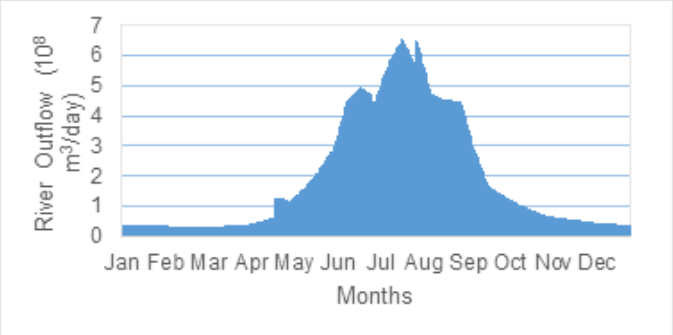

Fig. 3 ANN input, planned daily outflow hydrograph of moderate hydrological year (2057)

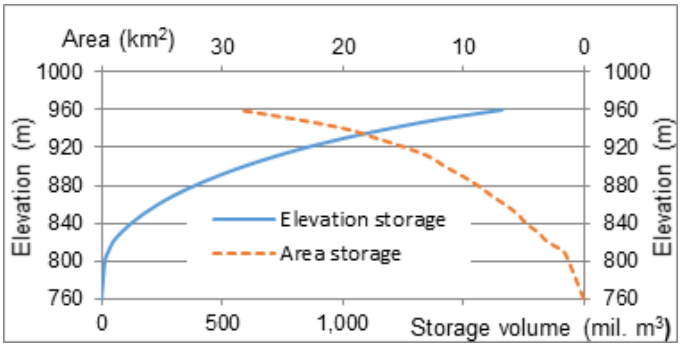

Fig. 4 Area-elevation-storage curve of Dasu HPP (Dasu Hydropower Consultants, 2013)

Assuming similar hydro-metrological conditions, daily river inflow at dam site from 1969-2008 was used as input parameter in the model for the period 2027-2066. In the inflow data, the moderate hydrological season was 1999 with peak daily discharge of 7.07×10^8 m^3/day (Fig. 2). Just one year later, 2000 was the driest season with a peak daily discharge of 5.06×10^8 m^3/day. The year 2006 was the wettest season with a peak daily discharge of 9.04×10^8 m^3/day. The difference between peak flows of the wettest and driest season was 3.97×10^8 m^3/day. River outflow from the reservoir was calculated based on reservoir operation guidelines of Dasu Hydropower Project. In the outflow hydrograph, 2057 was the moderate hydrological season (Fig. 3). In the outflow hydrograph the wettest seasons were 2064, 2043, 2040, 2059, 2031, and 2038. The peak outflow discharge in 2064 was 9.04×10^8 m^3/day. The driest season in outflow hydrograph was 2058 with a peak outflow discharge of 4.8×10^8 m^3/day. The outflow of 4.8×10^8 m^3/day is comparatively lower than the inflow at the same period, i.e. 5.06×10^8 m^3/day. The difference in inflow and outflow hydrograph was due to filling of the dam to its full supply level after finishing the free flow flushing operation in monsoon at that period. The reservoir capacity was calculated from the area-capacity and elevation curve of the reservoir operation (Fig.4). Target for subject ANN model was sediment retained in the reservoir ponding area during 2027-2066, which was estimated by using HEC-RAS-1D numerical model. In HEC-RAS model, daily inflow discharges and reservoir water levels (RWL) were used as upper and lower boundary conditions, respectively. Acker-White sediment transport formula was used for sediment simulations in this model. Acker-White sediment transport formula showed better results for Dasu Hydropower Project, in previous studies conducted by Rehman et al. (2015). Yang et al. (2009) evaluated total load sediment transport formulas using ANN technique and it was found that ANN model is a reliable and uncomplicated method to predict total sediment transport rate of total bed material load transport rate. It was also found that the accuracy of Ackers and White (1973) sediment transport formula showed some preference in the study results (Yang et al. 2009). In

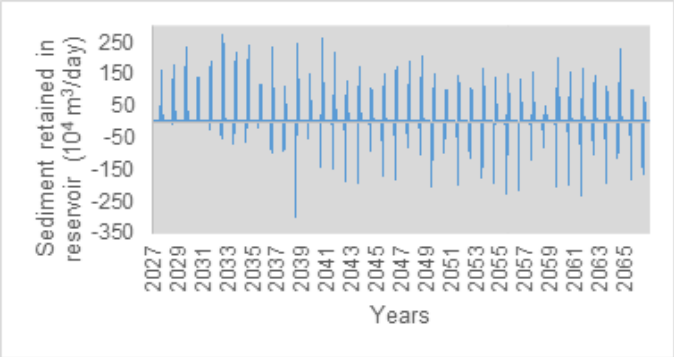

Fig. 5 ANN target, daily sediment retained in the reservoir ponding area (2027-2066)

constructed sediment retention graph (Fig. 5), the year 2038 was among the wettest seasons along with longer duration of high flows. In 2038, the monsoon started from the mid of April and ended in August. In normal years, the rotation of monsoon starts in the June and ended in August. The effect of longer duration high predicted more flushing of sediments from the dam (Fig. 5). The year 2066 showed highest peak of outflow but its duration of high flow event was only 20 days in June. Therefore, in 2066 the flushing of sediments out of the dam body was an average as of the other years. The flushing operation in the starting years of the project was planned for the shorter time due to less accumulation of sediments in the dam.

The combination of both ANN and HEC-RAS models is shown in Fig. 6. The input and output parameters of both models were correspond to the same period. The HEC-RAS model output of volume of sediment retained in the reservoir was used as target in the ANN model. The aim of using HEC-RAS output as target in ANN model was to observe the efficiency of ANN model to predict reservoir sedimentation.

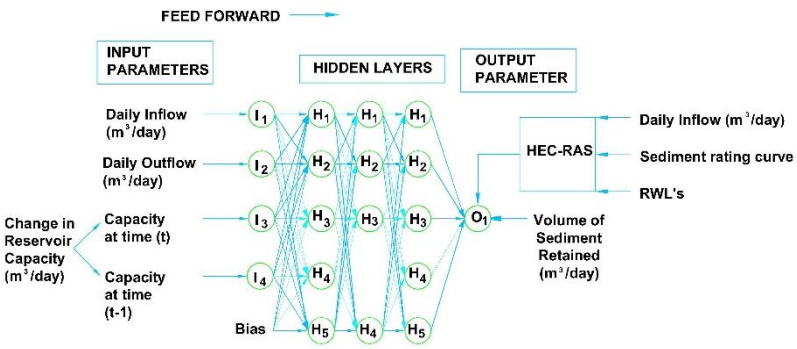

Fig. 6 ANN (4-5-4-5-1) architecture used in present study, with HEC-RAS output as target parameter.

2.2 ANN Model Development

The most commonly used artificial neural network in hydrological studies is feed forward neural network with back propagation (Agarwal et al. 2005). There is no fixed rule for the development of an ANN model, even though a general framework can be followed based on previous successful applications in engineering (Jothiprakash et al. 2009). In the present study of Dasu HPP, three types of multilayers perceptron (MLP) of ANN model architecture were developed to estimate reservoir sedimentation using 40 year's data.

Trial and error method was used to select an appropriate ANN architecture. Input parameters such as river inflow, river outflow, and change in storage capacity of the reservoir, for the model, were decided on the basis of available data and possible factors which can affect sediment retention (Eq. 3). Number of hidden layers and size of hidden layers were selected on trial and error basis. The number and size of hidden layers affect the performance of ANN, significantly. Random, Levenberg-Marquardt 'trainlm', and means squared error functions were used for data division, training and performance of ANN algorithms.

The 'trainlm' training function was used as training function in the developed ANN architectures. Permutations of logsig, tansig, radbas and purelin transfer functions in hidden and output layers were used to obtain the best possible solution.

a. Training and Validation of an ANN

In multilayer perceptron, artificial neural network, connections exist between different nodes of different layers and there is no connection exists within the same layer. The inputs are fed through the input layer and the output layer produced output after going through different training, testing functions in the input, hidden and the output layers. Between different layers there is a connection which is updated during the learning process by bias and synaptic weights. At initially, networks use small random values for training. In gradient decent algorithm, learning process stops when network attained to a steepest decent approach. Once the training process is satisfactory completed, the network was saved, the test and validation data set recalled and values predicted by the model were compared with the targeted data. When a comparison is within the satisfied limit, the network than the network is considered to be a well-trained network. For training purposes Levenberg-Marquardt algorithm was used as it has been widely used in approximating a complicated non-linear function (Wang et al. 2008). In the present study, the model was used to test the statistical indicators of coefficient of regression (R), root mean-square error (RMSE) and mean absolute error (MAE). The RMSE of the training period was the deciding parameter for the selection of corresponding performance parameters and ANN architecture (Fig. 7). Block diagram of 3-D array ANN architecture with three hidden layers as an example with the input and the output parameters is as shown in Fig. 7. Furthermore, ANN model sediment estimation error, per km^2 of the catchment area was estimated by using error to catchment area relationship:

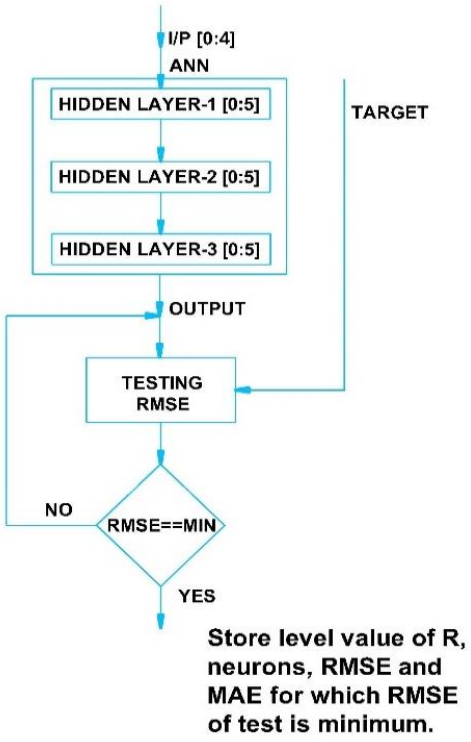

Fig. 7 ANN algorithm for correlation, RMSE and MAE.

$$Sediment\ estimation\ error, per\ km^2\ of\ cathment\ area = \frac{Error}{Catchment\ area} \quad (5)$$

b. Model Setup

Multilayer perceptron of artificial neural network architectures were developed by using MATLAB tool. Three feedforward network architectures of ANN having one, two and three hidden layers were tested for the current simulations. Input data was allocated to the model according to default, i.e. in random basis. 70% of the data set ($\Delta s, q_{w(in)}\ and\ q_{w(out)}$) was used for training, 15% for testing and the remaining 15% was used for validation. Trial and error method was used for selection of appropriate ANN architecture and number of neuron in the hidden layers. The one-hidden-layer ANN architecture was tested 100 times with 1 to 20 neurons in the hidden layer, the two-hidden-layers ANN architecture was tested 10 times with 1 to 10 neurons in the hidden layers, and the three-hidden-layers ANN architecture was tested 5

times with 1 to 5 neurons in the hidden layers, respectively. The output for each simulation was daily volume of sediment retained in the reservoir. After specifying the whole arrangement, the programme was simulated to find out the best combinations of different performance statistics (R, RMSE & MAE). Statistical performance of respective ANN architectures output and used functions were stored after each simulation and best results were sorted out after finishing the whole simulation process as an example of the four layers ANN algorithm is shown in Fig. 7. To get visualization of the model performance, a comparison was made between the best performed ANN architecture for predicting the sediment retained.

3. Results and discussions

The results of the three tested architectural cases were categorised on the basis of number of layers in each architecture. Case-I contains the one-hidden-layer ANN architecture results, case-II contains the two-hidden-layers ANN architecture results, and case-III contains the three-hidden-layers ANN architecture results.

3.1 Case-I

The one-hidden-layer neural network architecture was tested with four permutations of ‘logsig’, ‘tansig’, ‘radbas’, and ‘purelin’ transfer functions in the hidden and the output layers. RMSE in the testing period was the deciding factor of selecting the suitable ANN architecture. For this case, the minimum RMSE was found by using ‘logsig’ and ‘purelin’ transfer functions in the hidden and the output layers, i.e. 1.86×10^5 m^3. The value of RMSE 1.86×10^5 m^3 was comparatively lower than the value of RMSE by using ‘tansig’ and ‘radbas’ transfer functions in the hidden layers. The ‘tansig’ and ‘logsig’ transfer functions showed maximum RMSE, i.e. 2.7×10^5 m^3. Similarly ‘logsig’ transfer function in both, hidden and output layers also showed higher RMSE, i.e. 2.3×10^5 m^3. Number of neurons in the hidden layer of the best performed ANN architecture were 14. This ANN provided correlations of 0.92 and 0.90 for the testing and training data set, respectively.

3.2 Case–II

The same procedure was repeated for the two hidden layers neural network and it was tested with permutation of ‘logsig’, ‘tansig’, ‘radbas’ and ‘purelin’ transfer functions in the hidden and the output layers. In this case using transfer functions of ‘tansig’, in both hidden layers and ‘purelin’ in the output layer predicted efficient results for RMSE of testing, i.e. 1.88×10^5 m^3. In this ANN architecture combination, number of neurons in two hidden layers were 8 and 10. The correlation coefficients for testing and training periods were 0.92 and 0.91, respectively.

3.3 Case-III

The three hidden layers ANN architecture was simulated with 30 different combinations of transfer functions of ‘logsig’, ‘tansig’, ‘radbas’ and ‘purelin’. The minimum RMSE of the testing period for case-III was obtained with ‘logsig’ transfer function in all three hidden layers and ’purelin’ transfer function in the output layers (1.86×10^5 m^3). The numbers of neurons in the respective hidden layers were 5, 4, and 5. For the testing and training period, the correlation coefficients were 0.92 and 0.91, respectively.

In efficiently performed ANN architectures, the most common factor among all the results was the transfer functions (Tab. 1). The ‘purelin’ transfer function in output layers predicted efficient results of RMSE of testing in the three layers neural architecture ANN (4-14-1), four layers

neural architecture ANN (4-8-10-1), and the five layer neural network ANN (4-5-4-5-1): i.e. $1.86x10^5$ m^3, $1.88x10^5$ m^3, and $1.86x10^5$ m^3. The ANN (4-14-1) and the ANN (4-5-4-5-1) architecture used 'logsig' transfer functions in all hidden layers. Thus the RMSE of testing of these architectures is almost similar. The RMSE of three layers neural network with 'logsig' transfer function in both hidden layers and 'purelin' transfer function in the output layer was $1.93x10^5$ m^3. That is higher than RMSE with 'tansig' transfer function in the both hidden layers and 'purelin' transfer function in the output layer, i.e. $1.88x10^5$ m^3. Therefore, in four layers neural network, the best transfer function in hidden layer was 'tansig' while the best transfer function in three and five layers neural network was 'logsig'. Among the performance parameters of RMSE for testing and validation periods, ANN (4-14-1) performed better. Again, in MAE of training, ANN (4-14-1) performed better. ANN (4-5-4-5-1) performed better in MAE of testing, i.e. 8.17 $x10^4$ m^3. Although, RMSE of training as well as MAE of testing and validation were not the deciding parameters of selecting the appropriate neural network structure, these parameters reveal the performance of selected architectures. Among the best three selected architectures, ANN (4-14-1) performed better and ANN (4-8-10-1) was at the last in performance statistics. It may be possible that neural network architectures with one hidden layer and 1 to 20 neurons in the hidden layer were tested and recorded 100 times to get best results. The neural network architectures with two hidden layers and 1 to 10 neurons in the hidden layers were tested and recorded 10 times to get the best results. The neural network architectures with three hidden layers and 1 to 5 neurons in the hidden layers were tested and recorded only 5 times to get the best results. Thus, the two and the three hidden layers neural network predicted best results by utilizing the maximum allowed number of neurons, i.e. 8, 10 in the two hidden layers neural network and 5, 4, 5 in the three hidden layers neural network. Therefore, it could be possible that by increasing the number of neurons in the hidden layers of three and four layers neural network may improve the efficiency of these ANN architectures. However, increasing the number of neurons or size of neural networks utilize more power, time, and memory. In current simulations of three and four hidden layers neural network, the elapsed time was 7,322 and 17,238 seconds. Thus, selection of appropriate neural network architectures always require a compromise between cost and efficiency.

Tab. 1 Summary of performance statistics of efficient ANN architectures

ANN Architecture	Transfer Function in				Performance Parameters					
	Hidden Layer-1	Hidden Layer-2	Hidden Layer-3	Output Layer	R-tes.	R-val.	RMSE-tes. (10^5 m^3)	RMSE-val. (10^5 m^3)	MAE-tes. (10^4 m^3)	MAE-val. (10^4 m^3)
ANN(4-14-1)	logsig	No Layer	No Layer	purelin	0.926	0.905	1.860	2.146	8.224	9.259
ANN(4-8-10-1)	tansig	tansig	No Layer	purelin	0.924	0.909	1.884	2.159	8.299	9.347
ANN(4-5-4-5-1)	logsig	logsig	logsig	purelin	0.923	0.908	1.863	2.229	8.177	10.061

The study on reservoir sedimentation estimation by using the artificial neural network was conducted (Jothiprakash et al. 2009) for the Gobindsagar Reservoir on the Satluj River in India. The Satluj River is a tributary of the Indus River Basin System (Singh and Jain 1993). Jothiprakash et al. (2009) employed annual rainfall, inflow, and reservoir capacity of 1971 to 2003, as an input parameters in ANN (3-5-1) model and determining the volume of sediment retained in the reservoir was the target and the output of the model. The study results showed that the RMSE and MAE of the testing periods of ANN (3-5-1) for the Gobindsagar Dam, with a catchment area of 56,876 km^2, were $3.51x10^6$ m^3 and $3.14x10^6$ m^3, respectively. Per square kilometre catchment area RMSE and MAE of testing periods, for the Gobindsagar reservoir were about 61.76 m^3 and 55.26 m^3. In the present study of Dasu HPP, RMSE and MAE of the testing periods of ANN (4-14-1) were $1.86x10^5$ m^3 and $8.22x10^4$ m^3. Similarly, catchment area

sedimentation estimation error per km^2 during the testing period, for RMSE and MAE were 1.17 m^3/km^2 and 0.51 m^3/km^2, respectively (Tab. 2)

Tab. 2 Comparison of ANN performance statistics of the Dasu HPP with the Gobindsagar Dam

Dam	RMSE-tes. (10^6 m^3)	MAE-tes. (10^6 m^3)	CA (km^2)	RMSE-test/CA (m^3/km^2)	MAE-test/CA (m^3/km^2)
Dasu	0.186	0.082	158,800	1.17	0.51
Gobindsagar	3.51	3.14	56,876	61.76	55.26

CA: catchment area

The model predictions of ANN (4-14-1) for Dasu Hydropower Project showed statistical preferences over ANN (3-5-1) model predictions of existing Gobindsagar Dam. It may possible due to differences in input parameters and time duration of input data sets. In Gobindsagar Dam (Jothiprakash et al. 2009) annual rainfall, annual inflow and annual capacity was used as input parameter while in the present study daily data of inflow, outflow and capacity was used as input parameter. The length of data sets in Gobindsagar Dam and Dasu HPP were 32 years and 40 years, respectively. The catchment area of Dasu is almost 2.8 times more than Gobindsagar Dam's catchment area. Therefore, it seems that the interval of data set and catchment area effects the efficiency of ANN.

A comparison of optimal performed ANN architecture predictions with target sediment volume retained in the reservoir ponding area showed that the model prediction in all three best ANN architectures, i.e. ANN (4-14-1), ANN (4-8-10-1) and ANN (4-5-4-5-1), captured well the sediment retention and flushing in the dam ponding. Comparison of targeted and best performed ANN (4-14-1) network model estimation for the testing period is shown in Figure 8. At the beginning, ANN model deviated from the target sediment retention. The possible reason behind deviated trend may be the training of ANN. The ANN model was trained with input data on randomly basis. Furthermore, there was no flushing operation planned in the initial five years of the project, the only sediment flushing was due to high flows in the river during monsoon period. After five years the flushing operation was repeated every year in the dam. After training well, the ANN predicted well the sediment retention and flushing operations in the dam as showed in both testing and all periods of Fig. 8 (a) and Fig. 8 (b). To visualize the sediment retention trend of ANN (4-14-1) model predictions in wettest and moderate hydrological seasons, a comparison of results is made in Fig. 9. It was noticed that ANN (4-14-1) captured well the overall trend of sediment retention in the reservoir and flushing out of the reservoir (Fig. 9 (a)). The year 2057 was the moderate hydrological year and in sectional view of Fig. 9 (b), the model predicted well both processes of sediment flushing and sediment retention during the filling of the reservoir. Similarly, the year 2064 was the wettest season with highest peak of discharge of 20 days, that high event was also well captured by the model as shown in Fig. 9 (c). The year 2038 was also wettest season with longer peaks of high flows due to pre start of monsoon and that trend was also captured well in the model. During these year more flushing was predicted both in target and ANN (4-14-1) as shown in Fig. 9 (d).

4. Conclusions

The developed artificial neural network could well capture the pattern of the volumes of sediment deposited in the reservoir and flushed out of the reservoir on a daily basis for Dasu

Hydropower Project (DHP). The best MPL of ANN (4-14-1) was with 'logsig' transfer function in the hidden layer and 'purelin' transfer function in the output layer. This ANN also captured well the events of sedimentation in wettest and driest hydrological seasons of the Project. It was observed that with longer length of data set of shorter intervals could improve the efficiency of the ANN model. Furthermore, the catchment area of the watershed also influenced the performance parameters of the model outcome. It was also observed that increasing the size of neural network for long duration data set of shorter intervals did not affect the statistical performance of the model. It was concluded that the artificial neural network is a good tool for the estimation of sediment deposition within the reservoir ponding area and estimation of sediment flushing out of the reservoir for the Dasu Hydropower Project.

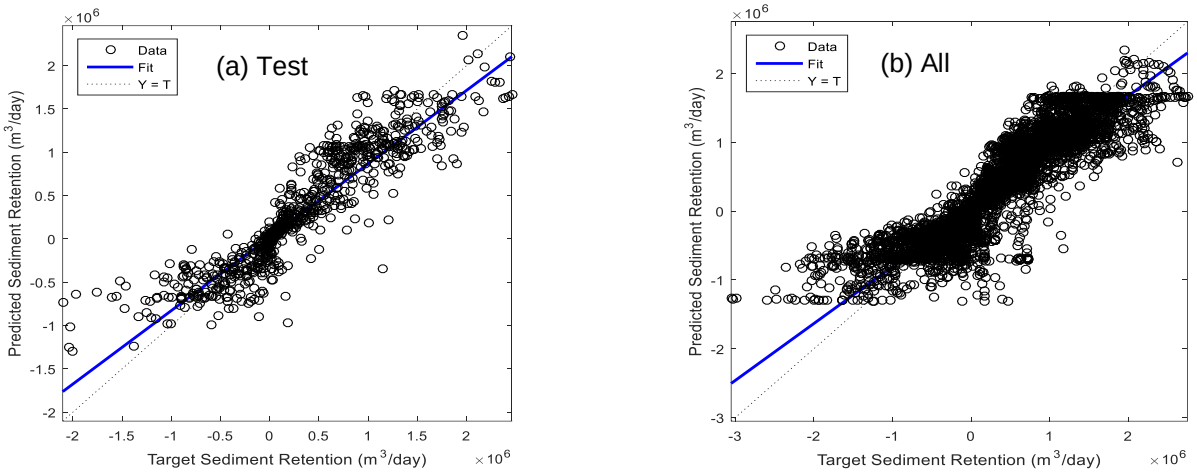

Fig. 8 Comparison of sediment estimation by ANN (4-14-1) model with the targeted data

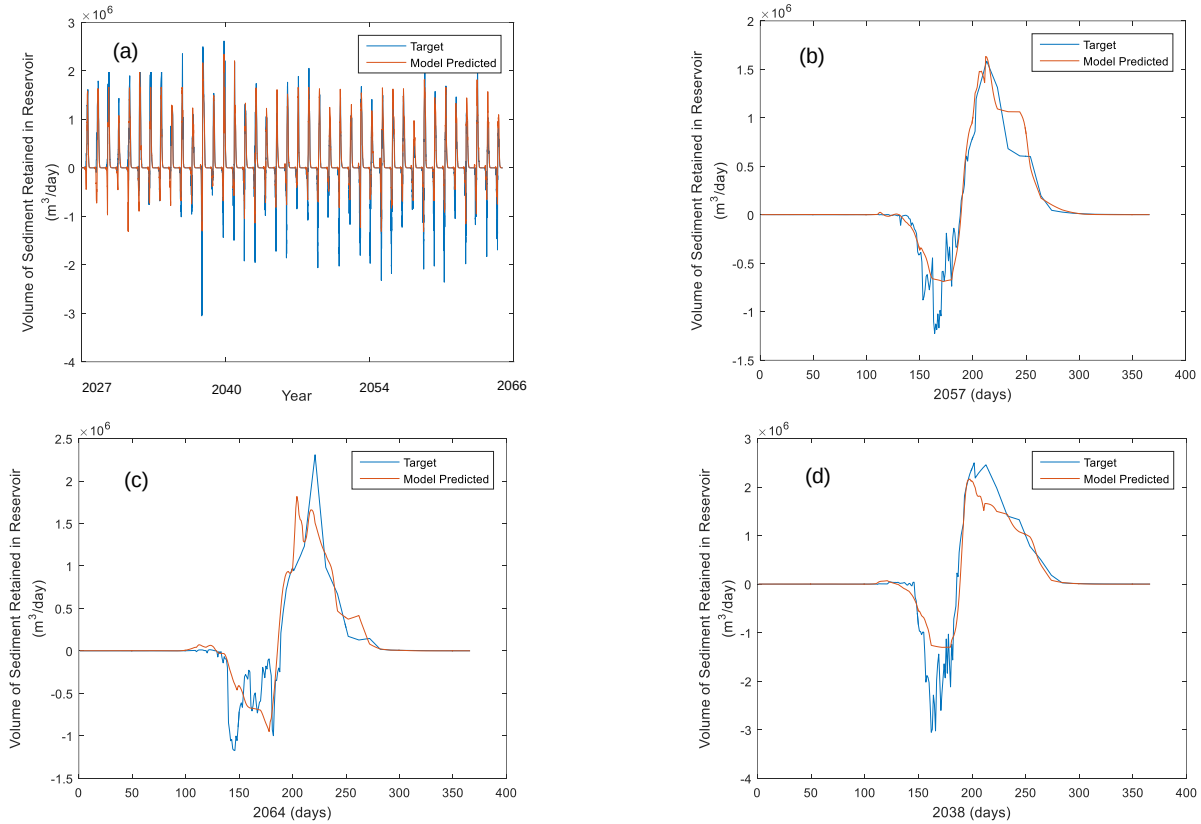

Fig. 9 Comparison of sediment estimation by ANN (4-14-1) model with the targeted data in (a) all, (b) moderate, (c) wettest with high peak, and (d) wettest with long duration, hydrological cycles.

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