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Sedimentation Estimation Study Using Artificial Neural Network for Karaj Dam Reservoir in Iran

Mohsen Salimi[1*], Yousef Hassanzadeh[2], Rasoul Daneshfaraz[3] and Mahdi Salimi[4]

[1]Department of Engineering, Maragheh Branch, Islamic Azad University, Maragheh, Iran
[2]Faculty of Civil Engineering, University of Tabriz, Tabriz, Iran
[3]Civil Engineering Group Technical and Engineering Faculty, University of Maragheh, Iran
[4]Department of Engineering, Ardabil Branch, Islamic Azad University, Ardabil, Iran

ABSTRACT

All reservoirs are subjected to sediment inflow and deposition up to a certain extent leading to reduction in their capacity. In this paper, a simple model has been developed for estimation of the sediment volume retained in the Karaj (Amirkabir) reservoir in Iran. In the present study, with considering sedimentation process, annual parameters related to rainfall, inflow and outflow values, are categorized as model input parameters and retained sediment volume was regarded as an output one.Since 32 years, available annual data for Amirkabir reservoir, 23 years data was used for training and the remaining 9 years data used for, model testing. The pattern of the sediment volume retained in this reservoir was well captured by multi-layer perceptron (3-3-1) artificial neural network (ANN) model, using the feed forward back propagation algorithm with Levenberg Marquardt training function and sigmoid activation function for the hidden layer and linear function for the output one. Based on several performance indices like correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE), average absolute relative error (AARE) and efficiency coefficient (E), it was found that the ANN model is able to estimate volume of the sediment retained in the reservoir with better accuracy as compared to conventional regression analysis.

KEYWORDS: Sedimentation, reservoirs, artificial neural networks, regression.

1- INTRODUCTION

Dams are usually constructed for the development and management of water resources such as water storage, hydropower generation, flood control, municipal water supply and other purposes. Cutoff of the sediment transport by the dam can cause stream bed degradation, may accelerate rates of the bank failure. Impounding water after construction of the dam will form a reservoir upstream from the dam site and changes the flow regime of the river due to backwater flow effects. Subsequently, sediments are deposited [1].There are many variables that affect the hydraulics of flow and the nature of sediment transport in a natural stream. Greater understanding of the processes involved could yield considerable benefits in reservoir design and operation [2].Annual sedimentation average rate is variable in different regions in the world. Reservoirs annual storage lost capacity is typically 0.1 to 2.3 percent due to sedimentation. Unfortunately, sedimentation rate is high in countries with large population[3]. The US reservoirs annual average rate of lost capacity is 0.2 percent which is evaluated to be more in low capacity dams [4].

The rate of sedimentation for some reservoirs of Iran has been reported in [5]. Considering Table1, it can be seen that, the annual average lost capacity in Iranis completely greater than the US reservoirs.

Table1. Annual average lost capacity in some Iran reservoirs [5]

Reservoir	Capacity ($10^6 m^3$)	Catchment area($10^6 m^3$)	Annual inflow ($10^6 m^3$)	Annual average lost capacity (percent)
Sefidrud	1800	58000	4500	2.2
Ekbatan	8	215	61	1.23
Latyan	95	1892	245	0.88
Dez	3340	17365	7442	0.51
Golpayegan	45	1050	80	0.24

So, importance of the sedimentation study is clear in Iran. Although in some empirical methods, catchment area, sedimentation rate and reservoir capacity parameters are used for sediment rate estimation, but Table1 indicates that there is not any clear relationship among these parameters.

In present paper, an intelligent model for estimation of the annual retained sediment volume (S_a) in Amirkabir reservoir is developed using ANN model. Three annual parameters including, rainfall (R_a), inflow

[*]**Corresponding Author:** Mohsen Salimi (MSc. Student of Hydraulic Structures), Department of Engineering, Maragheh Branch, Islamic Azad University, Maragheh, Iran. Email: salimi_mohsen@ymail.com

(I_a) and outflow (O_a)are considered as inputs, on the basis of their influence in sedimentation process. Unfortunately, the required annual hydrography results are available for just 1991 and 2007. So, S_a is determined by annual suspended sediment data from inlet and outlet stations of the reservoir, using Karaushev graph. Finally, it was found that the developed ANN method has well captured the trend of the retained sediment volume as compared to a traditional regression approach.

1-1- Study Area

The Karaj dam is located on the Karaj River in Varian Strait and 23 km from the city of Karaj with 850 km^2 catchment area. With 472 Mm^3 average annual inflow. It is a multi-purpose storage dam constructed for agricultural irrigation of Karaj plain, hydroelectric power generation and drinking water for Tehran. Amirkabir reservoir located in 52°5' to 51°8'E and 35°57' to 36°01'N, on the southern slope of the Alborz mountain. The Seera and Beylaghan are known as inlet and outlet stations, respectively. The watershed area is 718 km^2 at the inlet station. Karaj River total length is around 220 km. Fig.1 illustrates Amirkabir reservoir location. River slopesare 1.8 and 0.92 in Seera and Beylaghan stations, respectively [6].

1-2- Calculation of S_a: Retained Sediment Volume

For bed load estimation, there are several hydraulic and hydrological methods [7]. Considering that there is no suitable data for on-bed load of the Karaj dam, the Karaushev experimental curve has been used to determine bed to suspended load ratio based on the slope of the river (Fig.2) [7]. Studies show that the Karaushev theory is applicable on Iran Rivers [8].According to river slopes in the mentioned stations, calculation of the bed to suspend load ratios are resulted in 2 and 0.45 for Seera and Beylaghan stations, respectively.

Total sediment load has been determined by summation of the bed and suspended loads. By dividing the sediment mass to the average density of the sediments (1.4 ton/m^3 [6]), the volume of the sediment has been calculated. Subtraction of the inlet and outlet volume of sediments results in the deposited sediment volume in reservoir. Annual retained sediment values are obtained using Karaushev graph which are, assumed as an output parameter for both ANN and conventional regression method.

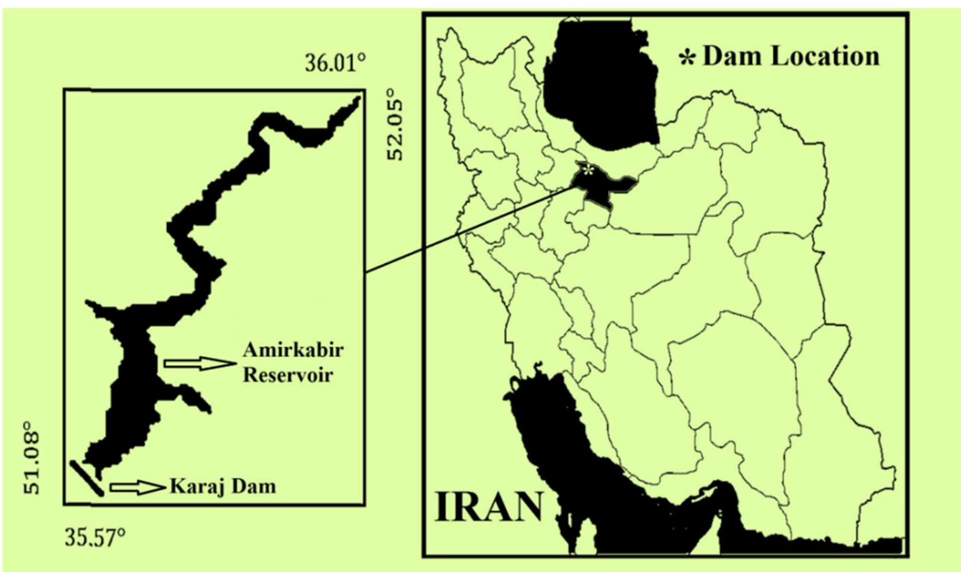

Figure1. Location of study area-Amirkabir reservoir

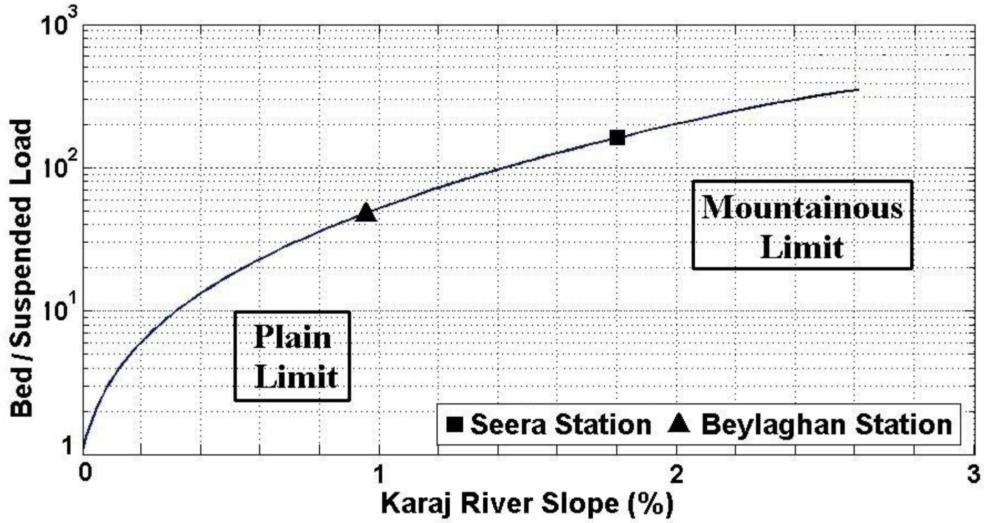

Figure2. Bed to suspended load ratios as a function of the river slope in Karaj [8]

Measured annual data for the period of 1980 to 2011 are used to carry out this study. Time series plot of the inputs (R_a, I_a and O_a) and output (S_a) are shown in Fig.3 and Fig.4. Input parameters are measured regularly by Iran Ministry of Power [6].

The correlation analysis of the available data is presented in Table2. According to this table, the strong relationship between S_a and I_a is obvious. In spite of weak correlation between input (R_a and O_a) with output (S_a) variables, considering previously published papers [9], R_a and O_a are used as input parameters.

2- MATERIALS AND METHODS

2-1- ANN Model

Since 1950s, estimation of the sedimentation rate has been subjected to several empirical studies. As a matter of fact, it has never been easy task due to complicated simultaneous involved processes such as sediment transport, erosion and deposition. In recent years, application of the artificial neural network technique has shown excellent performance in regression, especially in pattern recognition and function estimation [10]. Although, ANN method has been popular choice for sediment transport models, but limited studies have been conducted for sedimentation estimation in reservoirs using ANN or other nonlinear and intelligent approaches.

Dogan et al. compared ANN method for bed total load estimation with some conventional applications of the models [11].

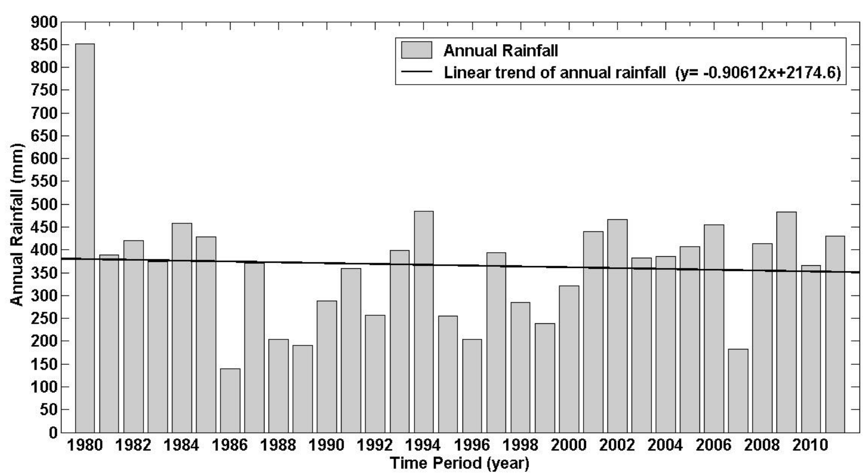

Figure3. Time series plot of the annual rainfall in Amirkabir reservoir

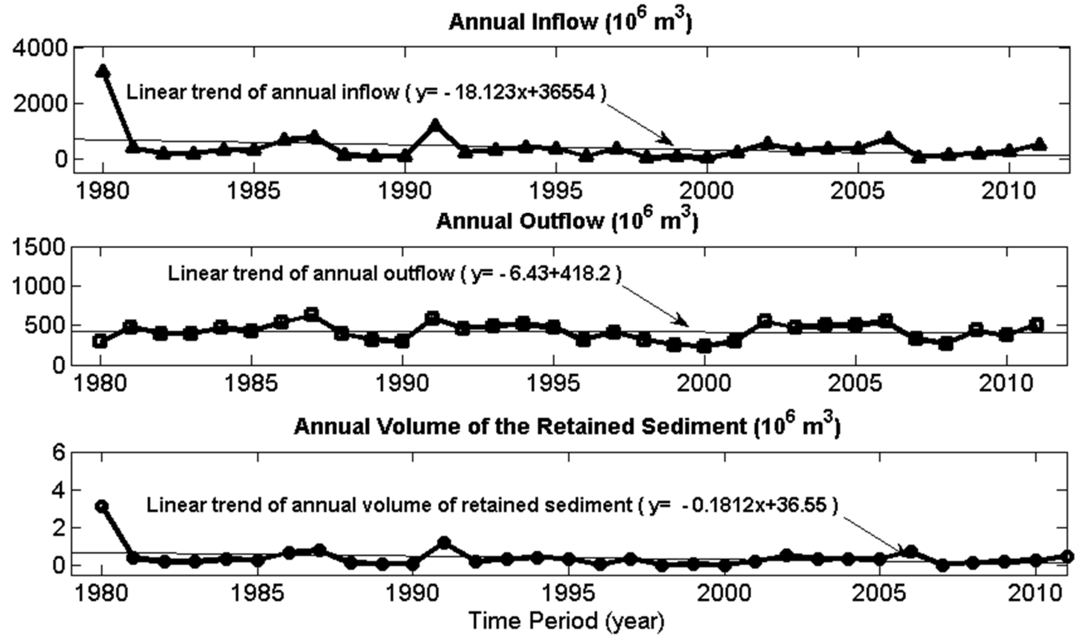

Figure4. Time series plot of the annual inflow, outflow and retained sediment volume in the Amirkabir reservoir

Considering rainfall intensity and outflow as input parameters and retained sediment as an output, Lee et al. applied back propagation (BP) algorithm, for reservoir lost capacity estimation. In [9], advantages of ANN method respect to a hydrological simulation program fortran (HSPF) numerical model is proved. Jothiprakash and Grag carried out an ANN model and a regression analysis for retained sediment estimation, using annual rainfall, annual inflow and capacity of Bhakra [12] reservoir as inputs. The volume of retained sediment in the reservoir was assumed as an output parameter. In [12], accuracy of the multi-layer perceptron (MLP) ANN model with one hidden layer was analyzed using some performance indices.

Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, vision and control systems [13]. In comparison with conventional methods, ANN is good at fitting functions. In fact, there is proof that a fairly simple neural network can fit any practical function [14].

2-2- ANN Model Development

There is no especial rule for ANN model development. This issue is fully covered in previously published application notes. In this paper, estimation of retained sediment volume of Amirkabir reservoir is based on MLP-ANN model selection. Trial and error approach has been employed to choose appropriate ANN architecture, the number of hidden layers and the number of nodes in each hidden layer. Corresponding to single output of the model, the sigmoid transfer function has been used for hidden layer and the linear function for the output one [12].It is necessary to mention that the performance of ANN model is significantly related to the number of hidden layer nodes.

It is completely well known that MLP-ANN consist if units arranged in layers. Each layer is composed of nodes and in the fully connected network considered here, each node connects to every node in subsequent layers [15].During the learning phase, the network learns by adjusting the weights so as to be able to predict the correct class output of the input signals [16].

Table2. Correlation analysis of available data

variables	R_a	I_a	O_a	S_a
R_a	1	-	-	-
I_a	0.6832	1	-	-
O_a	0.1109	0.5820	1	-
S_a	0.6959	0.8607	0.1740	1

It should be mentioned that, in the developed model, all of the considered data sets have been normalized in [-1,1] range. To normalize data, the following equation has been used which makes the entries standardized:

$$x_n = 2\left(\frac{x_i - x_{min}}{x_{max} - x_{min}}\right) - 1 \quad (1)$$

In this relation, x_n is the normalized data, x_i is the real amount of data, x_{min} and x_{max} are minimum and maximum entry data, respectively.

2-3- Networks Training and Validation

At first, the length of the used data-base during design process seems to be main weakness of the proposed model, but there are several reports which considered small such data-bases. For instance, Das and Basudhar, and also Lee et al., have reported satisfactory results based on this kind of data-base in 2006 in different papers [8,17].

In order to train and test proposed neural network model, available data are divided in two separate parts. Applied network algorithm is feed forward back propagation (FFBP) along with gradient descent with adaptive learning (GDA), gradient descent with momentum (GDM), Levenberg Marquardt (LM) and one step secant (OSS) training algorithms.

After each training process, predicted values have been compared with real or observed ones. Statistical indicators such as, correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE), average absolute relative error (AARE) and efficiency (E)have been used to evaluate performance of the model [18-20]. These five statistical indicators are used to evaluate effectiveness of the proposed method considering following measured data using following equations:

$$R = \frac{\sum_{i=1}^{n}(x_{obs}-\bar{x}_{obs})(x_{est}-\bar{x}_{est})}{\sqrt{\sum_{i=1}^{n}(x_{obs}-\bar{x}_{obs})^2(x_{est}-\bar{x}_{est})^2}} \quad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{obs}-x_{est})^2} \quad (3)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | x_{obs}-x_{est} | \quad (4)$$

$$AARE = \frac{1}{n}[\sum_{i=1}^{n}(1-\frac{x_{est}}{x_{obs}})] \times 100 \quad (5)$$

$$E = 1-\frac{\sum_{i=1}^{n}(x_{obs}-x_{est})^2}{\sum_{i=1}^{n}(x_{obs}-\bar{x}_{obs})^2} \quad (6)$$

In the above equations, x_{obs} is the observed parameter, x_{est} used for predicted parameter and n is the number of available data. Considering variable number of nodes in hidden layers, several structures have been formed using different training functions. Acceptable structure has been selected considering calculated performance indices for both training and test periods.

3- SIMULATION RESULTS AND DISCUSSIONS

In order to analyze proposed model and compare it with regression method, neural network toolbox of the *MATLAB v7.14* software has been used.

3-1- Analyze 1: Response of The Conventional Regression Approach.

Around 72 percent of available data have been used for design and remaining 28 percent for test purpose. For this analysis, obtained value of R is presented in Table3. It is obvious that the accuracy of this model can be improved by increasing number of the considered input variables.

Table3. Calculated value of the R based on conventional regression method

valueR		
Parameters	**Training**	**Testing**
R_a	0.7359	0.4707
I_a	0.8701	0.8825
O_a	0.0102	0.8576
R_a , I_a	0.8945	0.8348
R_a , O_a	0.7395	0.5499
R_a , I_a , O_a	0.9653	0.8711

Considering the regression method, the relation between inputs (R_a,I_a and O_a) and output(S_a) parameters can be written as following:

$$S_a = 0.0003R_a + 0.0048I_a - 0.0028O_a - 0.4293 \quad (7)$$

According to equation (7), performance indices can be calculated easily which are listed in Table4.

3-2- Analysis 2: Response of the ANN Method.

It is clear that regression approach cannot be considered as a convincing method. Hence, in this part reservoir retained sediment estimating is done using nonlinear ANN model selecting one hidden layer. Similar to conventional regression approach, randomly selected data have been used during training and testing periods.

Three nodes in hidden layer have been chosen by trial and error using defined training functions. Based on performance indices of the neural network model which is given in Table5, it is obvious that a MLP-ANN with 3-3-1 structure and LM training function is suitable for this purpose. Sigmoid and linear activation functions have been used for the hidden and output layers, respectively.

Comparing presented results in Table5, it is clear that the MLP 3-3-1 ANN model with mentioned architecture and functions has better performance. Detailed architecture of the proposed neural network model is shown in Fig.5 for retained sediment volume estimation.

Estimated and observed results for the output parameter (S_a) during test period is illustrated in Fig.6. It can be seen that output trend is well captured by proposed architecture. The scatter plot related to the observed and estimated data proves capability and effectiveness of the designed ANN model to predict the output parameter magnitude and trend (Fig.7).

According to reservoir hydrography results in 1991 to 2007 [6], measured sediment volume of the Amirkabir reservoir during these 16 years is equal to 6.9×10^6 m^3. Using developed model and with considering these two years, obtained value for this parameter is 6.5673×10^6 m^3 which shows 4.8217 % error.

3-3- Sensitivity Analysis

Sensitivity analysis is usually performed as a series of tests in which the modeler sets different parameter values to see how a change in the input parameter causes a change in the output one [21]. Typically, this technique concerns the mathematical method representation of a physical system and attempts to assess the sensitivity of the model outputs to variations of model inputs [22].

Table4. Calculated performance indices for multi-variable regression considering 3 inputs with an output

Performance criteria	Training	Testing
R	0.9653	0.8711
RMSE	0.1644	0.1799
MAE	0.1295	0.1227
AARE	1.1072	5.1142
E	0.9254	0.7314

Table5. Performance indices of MLP 3-3-1 ANN

Performance criteria	Training	Testing
R	0.9716	0.9882
RMSE	0.1501	0.0592
MAE	0.0587	0.0454
AARE	0.0731	0.426
E	0.9378	0.971

Lane and Ferreira [23] criterion have been defined sensitivity of the output related to input. Input variable is sensitive, if changes in it results in large error in the output variable (as large as or larger than the input changes). However, it is possible to define the maximum absolute difference (D_{max}) for i*th* input as:

$$D_{max} = \left| \frac{p_i^m - p_i^b}{P_i^b} \right| \times 100 \quad (8)$$

Where, p_i^m is the measured value of the output considering changes of i*th* input and p_i^b is the same prediction with corresponding base value. According to D_{max} value, sensitivity index (S_i) is listed in Table6.

Considering developed MLP 3-3-1 ANN model, results of the sensitivity analysis are presented in Table7. It is clear that in this study, all of the input parameters (R_a, I_a and O_a) have considerable effect on the output and hence, should be measured more accurately and precisely.

4- CONCLUSIONS

In this article, employed feed forward 3-3-1 structure and sigmoid activation function with LM training rule (function) well estimated Amirkabir reservoir sedimentation volume. The number of input parameters can be easily measurable at the reservoir and determined on basis of these parameters affecting the sedimentation process.

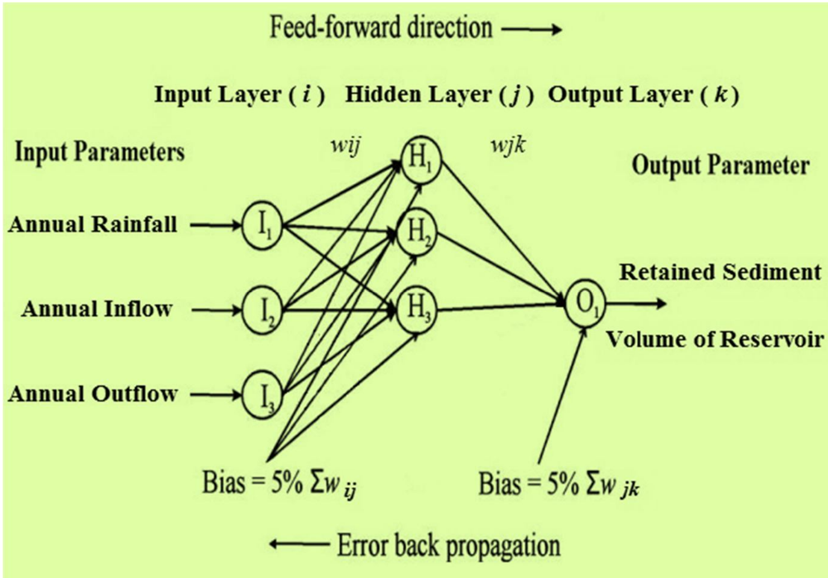

Figure5. Detailed architecture of the proposed model for Amirkabir reservoir sediment estimation

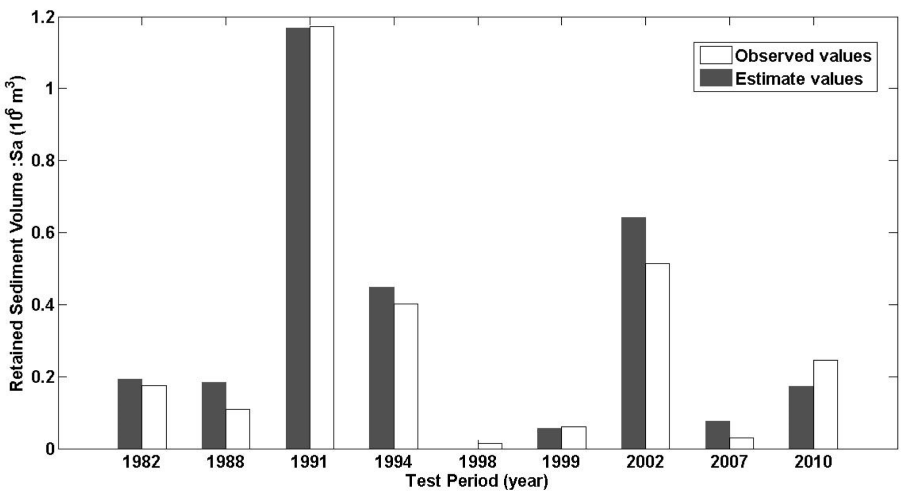

Figure6. Comparison of observed and estimated data using developed ANN model

Also, it is clear that large data-bases in Iran may improve ANN model for sediment yield prediction. Available ANN model can be used for future sediment volume prediction with high accuracy without need to measure output parameter.

Table6. Sensitivity index according to D_{max} intervals [23]

Statistics	D_{max}	S_i
Insensitive	0	0
Less sensitive	0-10	1
Sensitive	10-50	2
Much sensitive	<50	3

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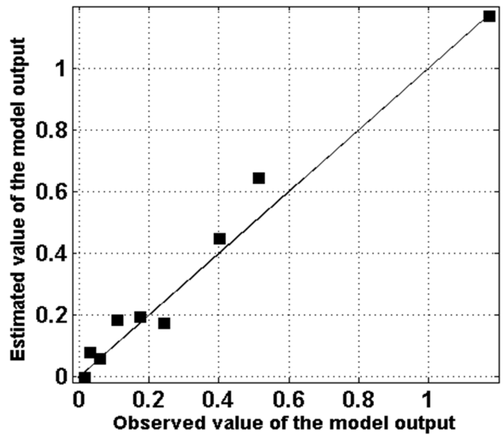

Figure7. Observed and estimated scatter plot of S_a for ANN model

Table7. Sensitivity analysis result for MLP 3-3-1 ANN model

Input parameters	D_{max}	S_i
R_a	82.51	3
I_a	258.25	3
O_a	321.08	3

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