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Comparing the Estimation of Suspended Load using Two Methods of Sediments Rating Curve and Artificial Neural Network (A Case Study: Cham Anjir Station, Lorestan Province)

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Abstract

It is significantly important to predict and estimate the sediment load of the rivers to manage rivers and dam reservoirs in water projects. In this study, the suspended load of the river is predicted using artificial neural network. In this paper, it is attempted to evaluate the performance of artificial neural networks in predicting the suspended sediments. Using ANN (Multilayer Layer Perceptron Model), the suspended sediment in hydrometric station of Cham Anjir river of Khorramabad has been predicted and the results have been compared with sediment rating curve. Based on the obtained results, ANN presents acceptable results in simulating the suspended load in Cham Anjir station, in such a way that it is of higher accuracy compared to sediment rating curve. The results showed that ANN could be employed to estimate the sediment suspended load with appropriate accuracy and more confidence compared to the rating curve. Here, it should be noted that neural network could not predict the peaks accurately, and this is regarded as a weak point of this model.

Keywords: Suspended Sediment, ANN, Sediment Rating Curve, Khorramabad River.

1 Introduction

As an intensifying process, erosion and sedimentation result in the loss of agricultural fertile soil and cause irreparable damages to constructive water projects, such as sediment accumulation behind dams and reducing their useful volume, destructing the structures, damaging the coasts and harbors, reducing the capacity and increasing the maintenance cost of irritation canals to name a few. On the other hand, sediment transfer affects the water quality indices with regard to potable and agricultural water. Therefore, estimating the amount of sediment is required in soil protection projects, designing and implementing water structures, watershed and utilizing water resources [7].

Jain (2001) used ANN to introduce the relation of sediment density in Mississippi river and proved that it gives more reliable results in comparison with other methods [8].

Cigizoglu (2002) compared the results from ANN with sediment rating curves to predict the density of suspended sediments [3].

The history of scientific investigations in the field of suspended sediment transfer in rivers is over a century, in such a way that the first sampling of suspended load from the rivers was conducted in 1845 in Mississippi River [16].

Kisi (2004) used different ANN techniques for predicting and estimating daily suspended sediment concentration and he indicated that multi-layer perceptron models performed better than the generalized regression neural networks and radial basis function networks [9].

Kisi (2005) employed ANN to model the suspended sediment load of flow. He also used sediment rating curves and a multi-regression model to predict the sediment load and showed that ANN produced the best results [10].

Using the measurement data of sediment suspended load and with the help of sediment rating models, it is possible to predict the transfer sediment. However, estimating the sediment using this model always associated some errors [2]. In addition, other researches have shown that estimating the suspended sediment using rating curves always associates with errors and it appears that the ANN model leads to fewer errors using rating curves [12]. Therefore, it is required to utilize smart methods such as ANN in estimating the amount of suspended load. To simulate the suspended load using ANN, two algorithms of back-propagation training algorithm and radial functions, they used the values obtained in these two methods to draw the sediment diagram and they realized that back-propagation training algorithms estimate the discharge of river’s sediment load more accurately [13]. Dehghani et al. 2009 compared the estimation of suspended load using two methods of sediment rating curve and ANN. The results showed that ANN could be utilized more accurately and confidently to estimate the sediment suspended load compared to rating curve with and without data classification [6]. Using the data of water discharge and sediment discharge simultaneously, in Galinak station in Talghan River, along with some geomorphologic

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parameters of the catchment area of this river, ANN was used to model the estimation of daily suspended sediment. The results of this study showed the higher accuracy of NN relative to regression models [15]. The common sampling method in most hydrometric stations is measuring the sediment suspended load. Then, the bed load is estimated as a percent of suspended load with regard to geomorphologic conditions of the river. However, the results of this procedure are not reliable [12]. It is required to have accurate information about the amount of sediment load of the whole river in many water resources projects such as estimating the sedimentation volume in dam reservoirs. In order to determine the total load of the floodway, numerous procedures have been proposed, each one of which are applicable in special conditions. Some of these relations are presented based on extending the equations of bed load. However, in addition to the need for special conditions, the calculated value of total sediment load using these relations is different from the measured values of total sediment load. The reason might be the effect of suspended load on total load value, and the suggested equations are not able to calculate it [7].

Melesse et al. (2011) estimated Suspended sediment loads for three major rivers (Mississippi, Missouri and Rio Grande) in USA using MLP modeling approach. Results from ANN model were compared with results from multiple linear regressions (MLR), multiple non-linear regressions (MNLR) and Autoregressive integrated moving average (ARIMA) using correlation coefficient (R), mean absolute percent error (MAPE) and model efficiency (E). The results show that the ANN predictions for most simulations were superior compared to predictions using MLR, MNLR and ARIMA [14].Therefore, there is a need to present new procedures, which could estimate total sediment load more accurately, without requiring special conditions to be applied. The aim of this study has been improving the estimation of total sediment load of the rivers using ANN (multilayer perceptron and radial base function).

Nomenclature

Q_S	discharge of suspended sediment (tons/day)
Q_w	discharge of its corresponding flow (m^3/s)
a , b	coefficients of the equation
Q_{obs}	observational discharge
Q_{est}	estimated discharge of neural network
Target	discharge of normalized suspended sediment
Output	estimated discharge of suspended sediment from neural network
X_n	expressive of normalized data
X	expressive of observational data
X_{min}	minimum value of observed data
X_{max}	maximum value of observed data
$\overline{X}_{est}$	mean of estimated data
$\overline{X}_{obs}$	mean of observational data
X_{est}	estimated data
X_{obs}	observational data
R^2	correlation between data
RMSE	Root mean square error
r^2	Nash coefficient

2 Material and Methods

2.1 Features of Catchment under Study

This study was conducted in Cham Anjir hydrometric station in the catchment of Khorramabad River, regarding the detailed statistics of the available concentration. The station is located in 33^o and $22^'$ north latitude with 1122 meter height and upstream catchment area of 1280 km^2. The statistical details of the catchment under study are shown in Table 1 and the catchment location is shown in Fig. 1.

2.2 Artificial Neural Network

Artificial neural network is a variant of artificial intelligence, which performs similar to human brain, albeit general and incomplete. In fact, ANN is an idea for data processing, which is inspired by bio-neural-system and processes the data similar to the brain. This system consists of numerous processing elements called neurons, which act coordinately to solve a problem. These neurons learn the problem's process through an example (observational data). In other words, they transfer data to the network structure through processing experimental data, knowledge or hidden rules. In fact, ANN is a math model, which is capable of modeling and creating nonlinear math relations for interpolation. In fact, ANN is trained through a limited series of real data and if the parameters, which affect the phenomenon under study, are selected accurately and given to the network, it could be expected to receive rational responses from the network [5]. The artificial neural network consists of the following sections:

1- Input layer: In this layer, inputs are connected to the outside world and the next layer of the network. No processing is performed in this layer.

2- Hidden layer: a layer in which processing occurs. The network could consist of one or more middle layers. The designer, often through trial and error process, obtains the number of layers and the number of nodes in each layer.

3- Output layer: in this layer, the outputs are connected to the outside world, in which the outside vectors are mapped and established. Often, back-propagation learning rule is employed to train the Multilayer Layer Perceptron (MLP) Neural Networks. In other words, the topology of the network is completed through back-propagation learning rule. Neural networks generally lack good interpolation. Therefore, this should be considered when selecting the training pattern. To do so, the patterns are classified into training and test patterns, before the neural network starts working. The training patterns should cover the data space as far as possible to produce better learning. It is obvious that the more the training patterns, the higher the generalization capability of promoting the network. Although training is a process that occurs during a relatively long time, but after generalization, it could present an output in lieu of each input rapidly.

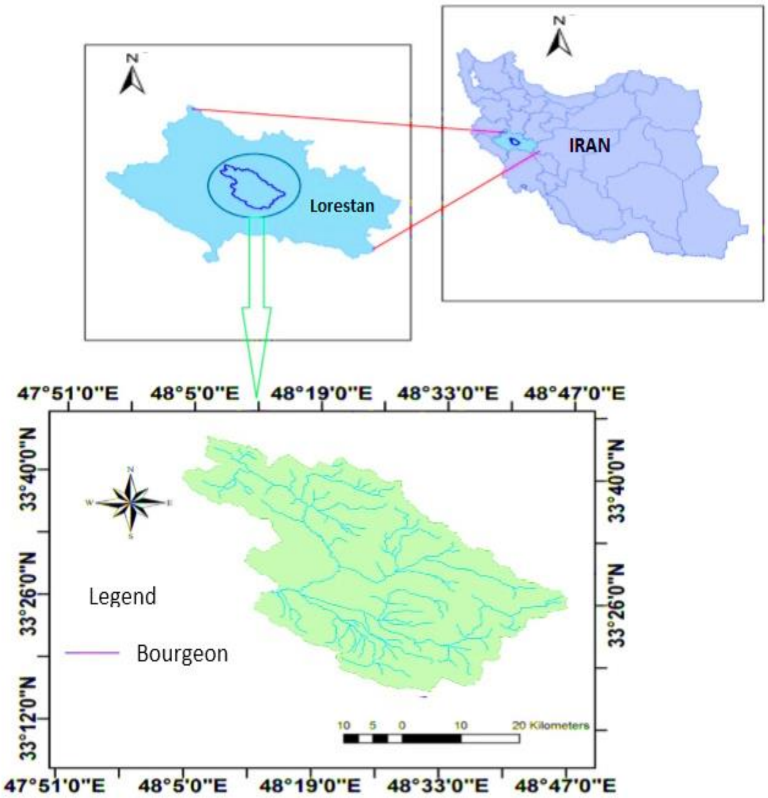

Fig. 1: The location of catchment area under study.

Table 1: Statistical details of flow discharge and sediment data in Cham Anjir station.

variable	mean	minimum	maximum	Standard deviation
flow discharge (m^3/s)	8.84	0.33	34.89	6.30
Sediment discharge (tons/day)	123.87	0.469	1597.844	217.1286

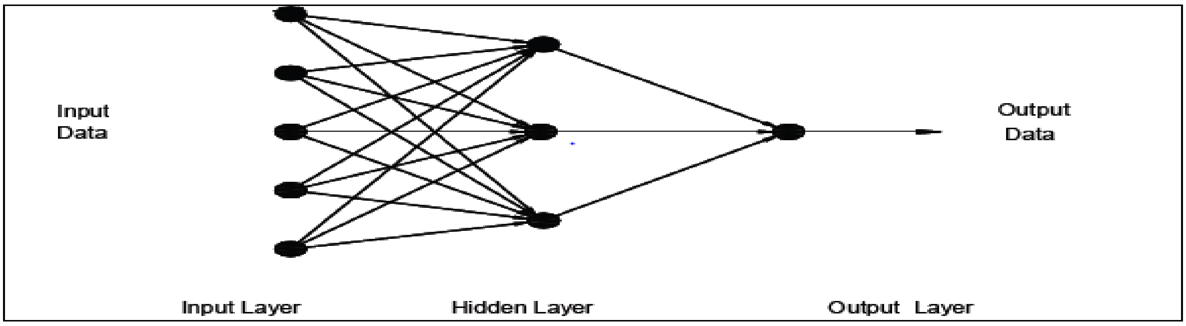

Fig. 2: The structure of Artificial Neural Network.

2.3 Sediment Rating Curve

Among common methods in estimating discharge of suspended sediment load in hydrometric stations is creating a connection between discharge data of the sediment and their corresponding discharge data, which is obtained through fitting of the curve between flow discharge values and their corresponding suspended sediment Eq. (1).

$$Q_S = aQ_w^{\ b} \qquad (1)$$

In addition, various methods are proposed to increase the accuracy of estimating the sediment through rating curve, among which is classifying the data in different shapes. Classifying the data could be used in the form of annual, seasonal, monthly, intermediate categories, classifieds discharge, similar hydrological cycle, and periods of low and high precipitation.

2.4 Data and Methods Used

In this study, the data and information available in Cham Anjir hydrometric station, Khorramabad, have been used. To do so, 473 corresponding data of flow discharge and sediment discharge are measured simultaneously. In artificial network methods, first, some data are selected to train the network, which are expressive of the conditions of the problem and other data are used to test the performance of trained network. The main point in selecting the training data is that it should cover a wide range of assorted data. In this study, 70% of the data were used as training data, data 15% for testing and 15% for testing the accuracy of the neural network model. An important fact in training neural networks is normalizing the data before being used in the model. This fact leads to better and faster training of the model, especially when the changing range of the inputs is high, because entering data in raw form reduces the speed and accuracy of the network. To normalize the data in this study Eq. (2), is employed.

$$X_n = \left(\frac{X - X_{min}}{X_{max} - X_{min}}\right) \quad (2)$$

Neural network was designed after selecting training data, testing and validation. To model the neural network, the software of MATLAB (Matrix Laboratory) was used. Among 473 data available, 331, 71 and 71 data were used for training, testing and validation, respectively. To achieve a suitable structure of artificial neural network, different models are designed and tested with different hidden layers and nodes and the related results were compared. After creating and testing different structures of the network and evaluating the obtained results, the final structure of the employed neural network for this study was selected, which was multilayer perceptron and back-propagation training method was used, which was simulated using MATLAB. The input and output layer of the network, which results in water discharge and output layer of sediment discharge, was used to evaluate the results from different models of artificial neural network and sediment rating curve method in addition to comparing the final results with observed values, along with 3 statistical parameters as follows:

$$R^2 = \frac{\sum\left(\left(X_{est} - \overline{X}_{est}\right) * \left(X_{obs} - \overline{X}_{obs}\right)\right)}{\sqrt{\sum\left(X_{est} - \overline{X}_{est}\right)^2) * \left(X_{obs} - \overline{X}_{obs}\right)^2}} \quad (3)$$

$$RMSE = \sqrt{\frac{\Sigma\left(X_{obs} - X_{est}\right)^2}{n}} \quad (4)$$

$$r^2 = 1 - \frac{\Sigma\left(X_{obs} - X_{est}\right)^2}{\Sigma\left(X_{est} - \overline{X}_{obs}\right)^2} \quad (5)$$

R^2 shows the correlation between data and the more and close to one is R^2, the more correlation exists among observational and estimated data. RMSE shows how much the estimated values deviate from observational data and the less is RMSE, the less is the deviation among the data and the more accurate are the results. Nash coefficient (r^2) is a statistical index, which shows the conformation ratio in hydrologic models. The value of this index is between 1 and$-\infty$. When it approaches one, the model has a better performance; if it is zero, it means that the model corresponds to the mean of the data; and when it is negative, the mean of the data is more efficient than the model [5].

3 Results and Discussion

3.1 Results from Artificial Neural Network

The results from the final model of neural network, used in this study, are shown in Fig. 3, 4 and 5 for test stage data along with related observational data.

As can be seen in Fig. 3, the neural network has lower or more estimation compared to observational values, which could be one of the weak points of neural network in estimating the suspended sediment. In other words, the neural network has simulated the suspended sediment related to the base and normal discharge, well. However, in simulating the sediment in flood events, it has not seen much successful. Results from Zhu et.al show this fact well.

3.2 Results from Sediment Rating Curve

As the study continued, the sediments were estimated through sediment rating curve to compare the results of neural network with the results of the common sediment rating curve method. In sediment rating curve, a regression relation is usually extracted between the data corresponding to the flow and sediment discharge. Then, based on this relation, the daily discharge value of suspended sediment is estimated for those days that the concentration of sediment is not measured.

In this study, the discharge and sediment data related to those days, which were used for modeling neural network for training, were drawn on a coordinates system to determine the sediment rating curve and obtain the line and equation related to the relation between discharge and suspended sediment. Fig. 6 shows the line and equation related to the rating curve. After obtaining the line equation in sediment rating curve method, data of the flow discharge related to the days, used in test stage of neural network, are placed in this equations, in such a way that all of the discharge data of test stage are placed separately in the equation resulted from the sediment rating curve.

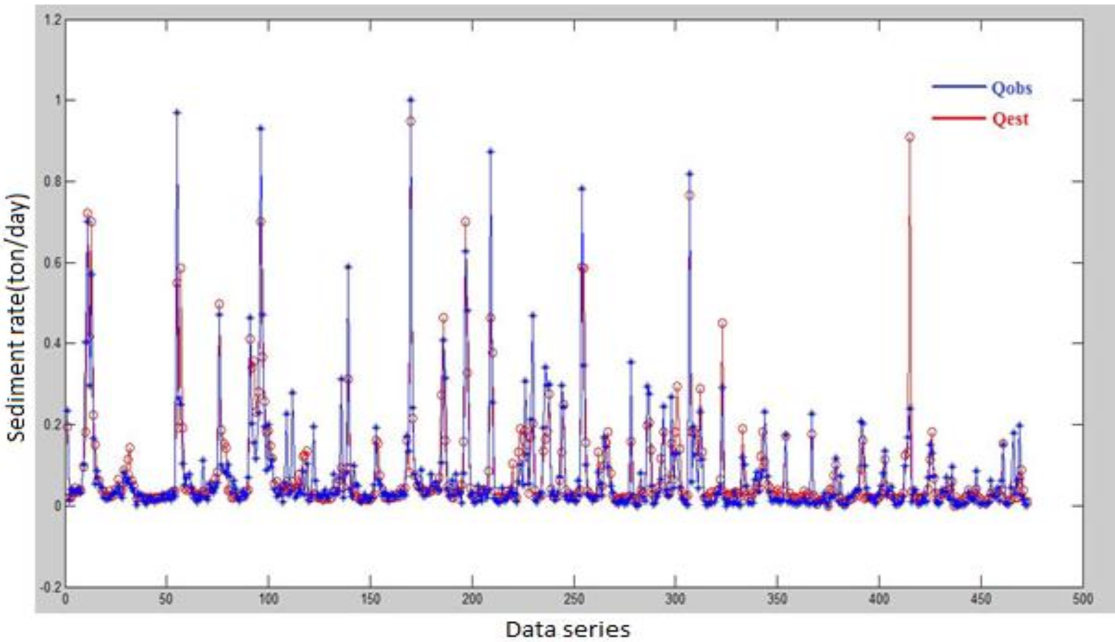

Fig. 3: Results from the simulation of suspended sediment using neural network against observational values

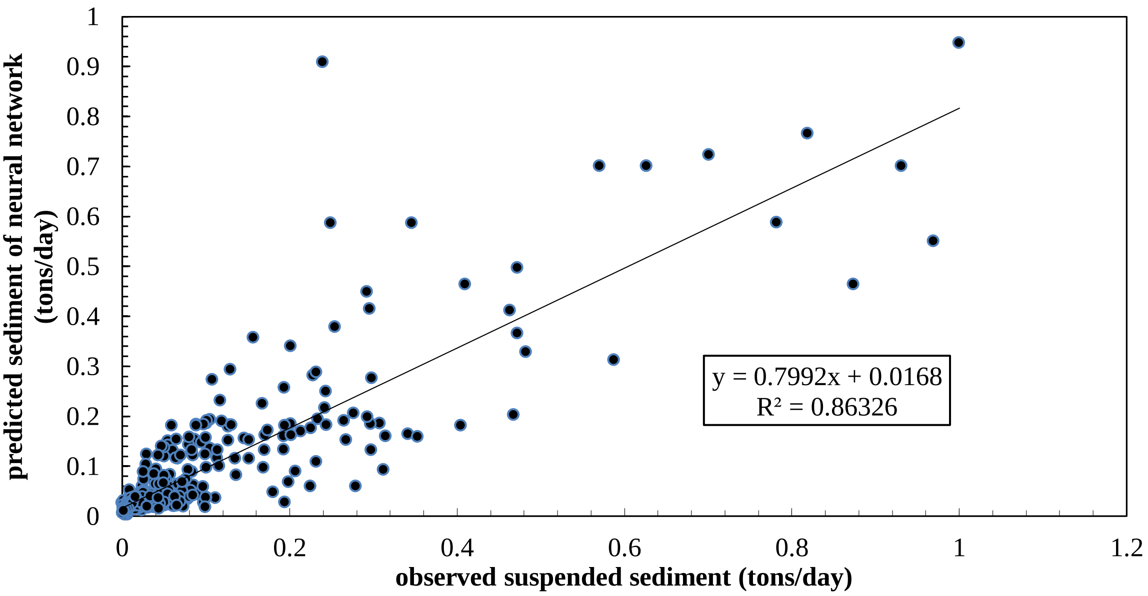

Fig. 4: The diagram of the results from the simulation of suspended sediment using neural network against observational values.

Then, the related corresponding sediment is calculated. In Fig. 7, the values of estimated sediment (based on sediment rating curve) are placed against the measured values. Comparing Fig. 4 and 7, which show the results of neural network and the common method of sediment rating curve, respectively, against observational data, shows the relative superiority of neural network method compared to sediment rating curve method.

The results of different statistical parameters such as R^2, RMSE and r^2, based on rating curve and artificial neural network, are shown in table 2. According to the Table, it could be observed that the neural network method presents the results with less error and higher correlation.

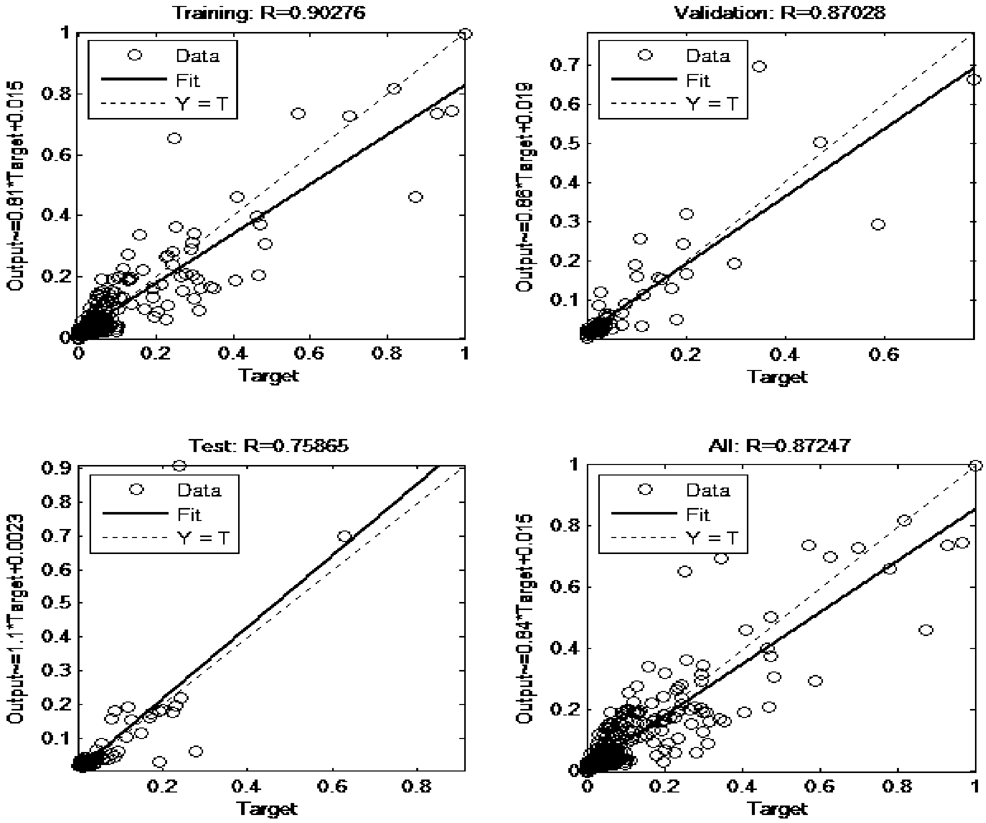

Fig. 5: Results from neural network in each stage of training, testing and validation.

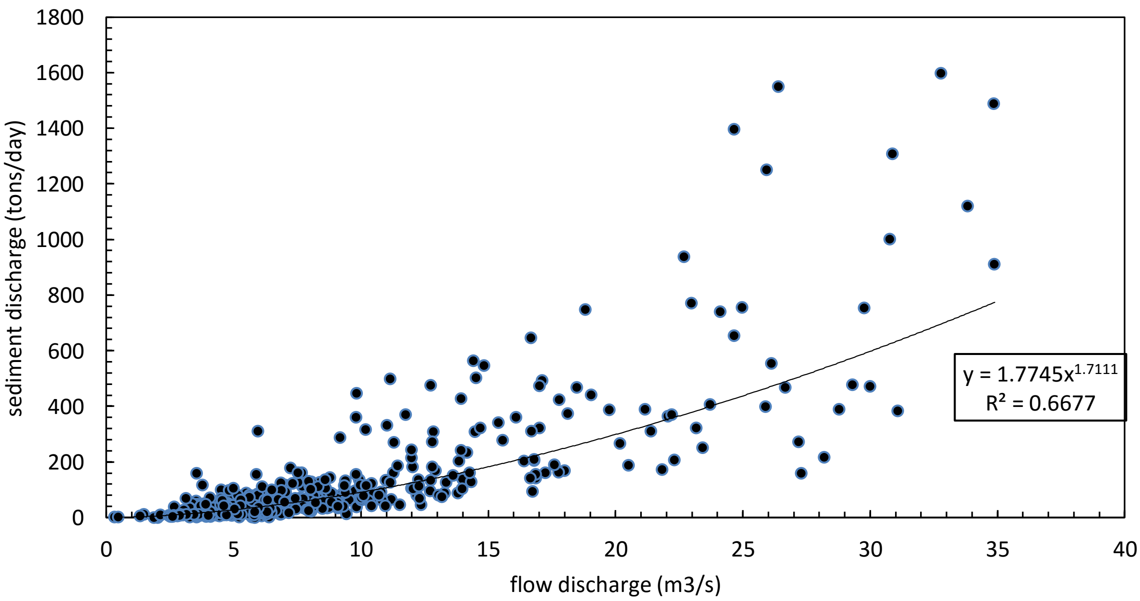

Fig. 6: Sediment rating curve and the line and equation obtained to estimate the sediment using this method.

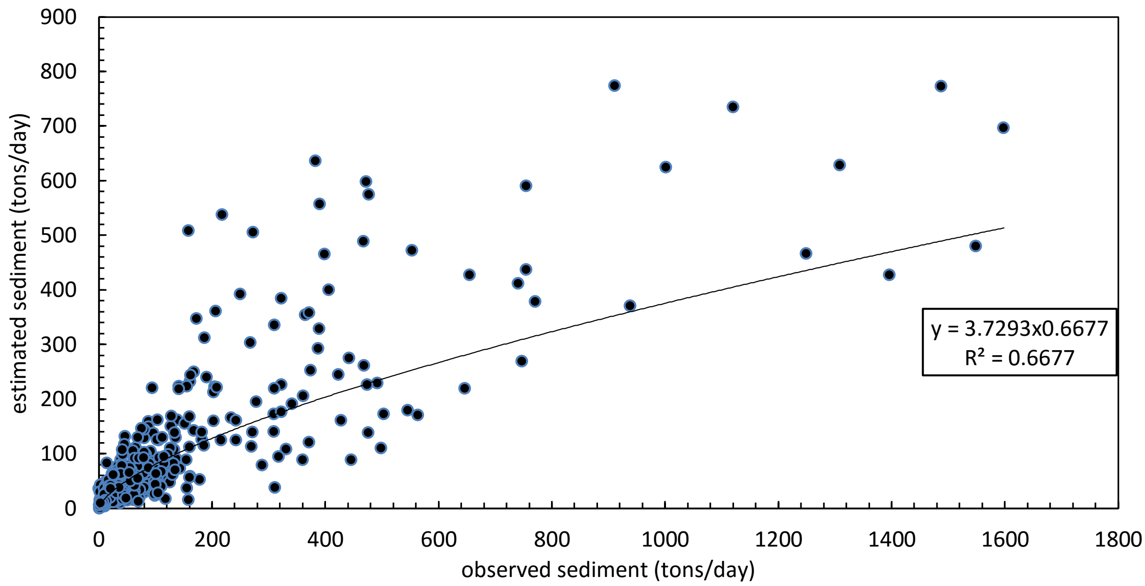

Fig. 7: The values of estimated suspended sediment based on sediment rating curve against observational values.

Table 2: Calculated statistical parameters related to neural network and rating curve.

Statistical parameters	Rating curve	Neural network
R^2	0.6677	0.87247
RMSE	0.152	0.0187
r^2	0.654	0.945

4 Conclusions

In this study, the application of neural network method and rating curve in estimating the amount of suspended sediment in Cham Anjir stations was investigated. To do so, two parameters were used as inputs and the model was simulated. The neural network presents acceptable results for simulation in Cham Anjir station in such a way that one of the statistical parameters to compare the accuracy of the model's estimations relative to observational data is R^2. R^2, obtained from the neural network, nearly equals 87% and R^2 resulted from sediment rating curve is nearly 67%, which shows the relative superiority of neural network compared to the rating curve. In fact, predicting and estimating this phenomenon is difficult and sometimes inaccurate. Since, in predicting the amount of sediments in the rivers different factors involve and in addition, it is a of a complicated nature: many problems related to suspended sediments in rivers could be solved through this method, since artificial intelligent methods are used to analyze those problems for which there is not enough knowledge or clear description. Certainly, it should be considered that neural network could not predict the peak points and this is considered as one of its weak points.

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