Estimations of Sediments in Mahabad Dam Using Artificial Neural Networks and Comparing the Results with Hydrometer Approach

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ABSTRACT: A deposition phenomenon is considered as one of the hydrometer processes which have ability to influence the most of the hydraulic structures and facility constructions. The exact assessment of the deposition of the rivers plays an important role not only in the management of the water sources, but also it is deemed that this factor also may have an influence on the designing, fabricating and planning phase of the utilization of Hydraulic Structures. In this survey, Neural Networks along with appropriate structure and self-training system is used as one of the methods of the estimating the amount of the sediments related to the Mahabad barrier, also the results of this survey are compared with the result of the hydrometer method. To this end, the discharge statistics of the water and sediments in two Cawter hydrometer station and Baitas village within the basin of Mahabad Dam catchment is investigated separately and at the end the estimation of the sediment load is compared and surveyed respectively by using neural networks in the Nero solution software via the multi-layer model of the Perceptron and the prevalent hydrometer approach. The results point out that the multi-layer networks in prognosticating a measure of the sediments is superior to hydrometer method.

Keywords: Artificial Neural Network, Hydrometer Method, Nero solution, Sediments.

INTRODUCTION

Sedimentation as an aggravated process, may lead to irreparable damages in the construction plans like accumulation of Sediments behind the barriers, occurrence of reduction in their valuable amount, destruction of constructions, damage to Ports and Coasts, reduction of capacity and increases in the maintenance expenditure related to the Irrigation canals. On the one hand, sediment transport is going to influence the quality of agriculture and drinking water, so the estimation of the sedimentation in soil conservation projects, designation and execution of the watery constructions, watershed and the utilization of the water sources is required and considered a very important factor (Abbasi Shushtary, 2006). The experts are always attempting to estimate the suspended sediment load in the stream of the rivers, for this purpose, first of all they should care about the state and the mechanism of moving sediments, then the amount of the transported sediments should be measured carefully in order to design and implement the watery plans with high confidence coefficient (Shafiyi Bajestan, 2005). The history of scientific investigation related to the suspended sediments, is more than 100 years (Waling and Web, 1981). By the use of the measurement data linked to the suspended sediments and with the help of the metrics models, experts can estimate the amount of the transported sediments, yet, the calculation of sediments via this equation, is always along with some errors (Sadeghi et al., 2008).

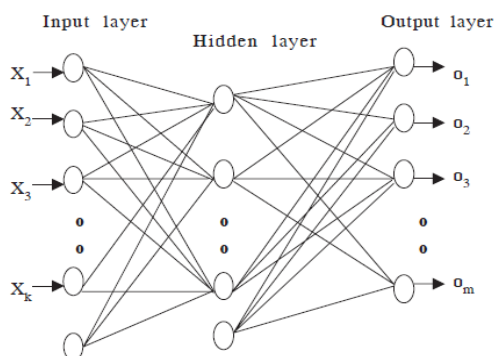The hydrological process, such as rainfall-sediment yield is extremely complex, non-linear, dynamic, and fragmented process due spatial variability of catchment characteristics, geomorphology and duration of the rainfall and involvement of other physical process. Artificial Neural Network (ANN) can be applied to predict the monthly, weekly and daily suspended sediment in the catchment by relating it to average rainfall, temperature, rainfall intensity and water discharge. Generally hydrological modeling using artificial neural network has adopted simple trained-and-tested procedure to find the best ANN structure. Sometimes due to inadequate data set, ANN structure is decided by this simple trained-and-tested procedure that provides biased testing. Cross validation procedure has been used for estimating the generalized performance for during smaller data set. Although suspended sediment load can be predicted using numerous developed equations their results often differ from each other and from measured data due to complexity of sediment transport nature. In recent years, simulation models for prediction of suspended sediment load of rivers have been popular among researchers because of Progress of computer models.

Piasy (1997) and Sadeghi et al. (2008) surveyed the role of raining, discharge within the recent days earlier than 10 days through the use of linear and nonlinear mechanical models in a watershed in India and Iran. The other survey which was conducted by Mosaedi et al. (2006) used artificial neural network for surmise of transport sediments at Tamar station which is placed in Gorganrud. The major structure of the network is based on the Perceptron model which offered better results when it is compared with sediment rating curves.

Many researchers have studied the application of Artificial Neural Networks in vital topics of hydrology and hydraulics such as prediction of sediment load, rainfall-runoff modeling, flow prediction etc. Cigizoglu (2002) made a comparison between ANNs and SRC for suspended sediment estimation and found that the estimations obtained by ANN's were significantly superior to the corresponding classical sediment rating curve ones. Agarwalet et al. (2006) simulated the runoff and sediment yield using artificial neural networks as daily, weekly, ten-daily, and monthly monsoon runoff and sediment yield from an Indian catchment using back propagation artificial neural network (BPANN) technique, and compared the results with observed values obtained from using single- and multi-input linear transfer function models. Including research similar Kisi (2005), (Montazer et al., 2003), Kumorjain (2001), (Avarideh et al., 2002), Zaker Moshfegh (2003), (Ghodsian et al., 2003), Najafi Hajivar et al. (2008), Yazdani et al. (2008), Verstraeten and Poesen, 2001), Zhou et al. (2002). Including similar studies can be the surveys which are done by Scholars like, Sarnagy with Tacharya (2005), Abul-Vaset and Sharadfard (2006), Firat and Kanger (2009), Hamdid and Kayalp (2011), Abasi Shushtari and Kashfipur (2006), Nayeeni et al. (2008), Melsi et al. (2011) to the following can be noted.

MATERIAL AND METHODS

There are numerous studies related to the application of ANNs to various problems frequently encountered in water resources. The nonlinear ANN approach was shown to provide a good representation of the rainfall-run off relationship (Hsu et al., 1995, Minns and Hall, 1996). The radial basis function type of ANNs to model the rainfall runoff process has also been examined (Fernando and Jayawardena, 1998; Fernando and Jayawardena, 1998; Mason et al., 1996). Campolo et al. (1999) used ANNs to forecast river flows during heavy rainfall and low-flow periods. ANNs were also considered to be a powerful tool for use in various groundwater problems (Ranjithan et al., 1993; Rogers and Dowla, 1994).

Figure 1. The structure of the artificial neural networks

The application of ANNs to sediment concentration Estimation is, however, not available in the literature. In this study, initially, ANNs are used to forecast the present or future sediment value using the past sediment values as input. The learning process or training forms the interconnection between neurons. The strength of these interconnections is adjusted using an error convergence technique so that a desired output will be produced for a known input pattern. Many training procedures are discussed in the literature. Error back propagation is one of the most commonly used procedures. The processing units are arranged in layers (Menhaj 2008).

Error evaluation criteria

The Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Relative Error (RE) are used to estimate the quality of results with measured data.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|(Y_{(actual)_i} - (Y_{(forcast)_j}\right| \qquad (1)$$

$$\text{RE} = \frac{(Y_{(actual)_i} - (Y_{(forcast)_j})}{Y_{actual}} \times 100 \qquad (2)$$
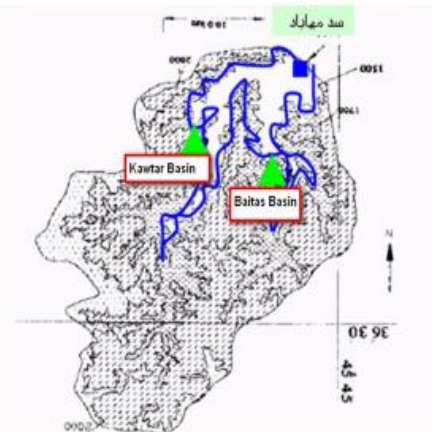
$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(Y_{(actual)_i} - (Y_{(forcast)_j})^2 \qquad (3)$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{(actual)_i} - (Y_{(forcast)_j})^2} \qquad (4)$$

Study area

The Mahabad catchment area is located in West Azerbaijan province and south Lake of Urmia. The length and north latitude of the basin is between 45 degrees and 25 minutes to 45 degrees 46 minutes and 36 degrees 26 minutes to 36 degrees to 46 minutes respectively. The area of this region is about 841 kilometer and the length of the main river is 61 kilometers. It should be stated that this basin is a little oblong with a relatively steep slope, and its altitude is 1363 kilometers. The average altitude in the desert is about 1400 meters and latitude from the sea level is 2000 meters. The main and prominent rivers of this catchment are the Baitas and Cawter which originates from the Heights located in the south and both of them are streaming parallel by ending in Mahabad barrier. After Mahabad dam they merge and form the Mahabad River which passes through Mahabad desert and it joins Lake Urmia.

The discharge statistics of the water and sediments in both Cawter hydrometer station and Baitas which placed in Mahabad dam catchment basin are investigated separately. At the end, by categorizing both rivers data on the basis of the upper and underneath discharge, the whole river was divided into four general categories.

Figure 2. The basin of the Mahabad Dam along with its hydrometer stations (Baitas and Cawter) and the real position of the Dam with its reservoir

Estimation of suspended sediments via sediments rating equations

Basically, there are two approaches in the estimation of the suspended sediment load. The first approach is based on the fitting of the one or few curves of the data. The most common of this approach is stated as power curve as follows:

$$Q_s = a.Q_w^b \qquad (1)$$

In the equation, Q_s is referring the sediment discharge and measured in ton/day, Q_w is the discharge of the water which is measured in m^3/s. In this equation a & b are the constant coefficients. The next approach is based on the use of mathematical models. In this approach the mathematical model is prepared according to the physical view of the issue and solution of hydrodynamic current. The mathematical models also are used in order to estimate the sediment. The use of this method may lead to numerous problems and difficulties. These models requirements are various data like grading materials, water temperature and its particular weight, flux rate, the section figure of the river, the substance of the wall and river slope. In most cases, all the data are not available and research may be conducted according to just the data of the discharge of water and sediments. So, as it can be inferred this model may lead engineers to encounter with some restrictions. Since these models are so distinct and the results that may be obtained are so different, the calculated values may be presented with serious uncertainty. This uncertainty will reduce the validity of the results.
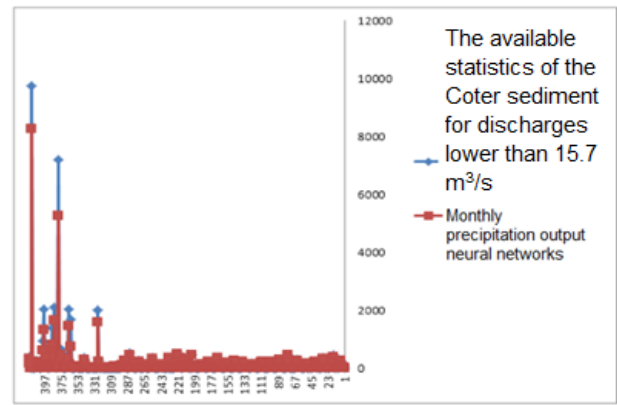
RESULTS AND DISCUSSION

The best result is obtained through a model which was based on the amount of the stream discharge as input layer and measured sediment as output layer. The results of the uses of the artificial neural network for estimating the sediment of the Mahabad barrier from the Cawter River over the trial and educating process for low discharges and high discharges of the 15.7 m^3/s are presented in Table 1. Also, in figures 3 and 4 the mentioned results are compared with real data of the sediment.

Figure 3. The performance of the artificial neural network in estimating the sediment of the Mahabad dam reservoir from the Cawter location for discharges lower than 15.7 m^3/s.

Figure 4. Artificial Neural network performance in estimation of the sediment of the Mahabad dam reservoir from the Cawter River location for discharges bigger than 15.7 m^3/s.

The results of the artificial neural network use in estimating sediments of the Mahabad dam that located in the Baitas River are presented in table 2-4. The best results obtained when the mentioned model was based on the discharge stream as an input layer and the measured sediment was considered as an output layer. The results of this model over the training and trial phases are presented in Table 2 for discharges lower and higher than 0.8 m^3/s.

Table 1. Results of the artificial neural network in estimating the sediments of the Mahabad dam over test and training phases related to the Cawter River
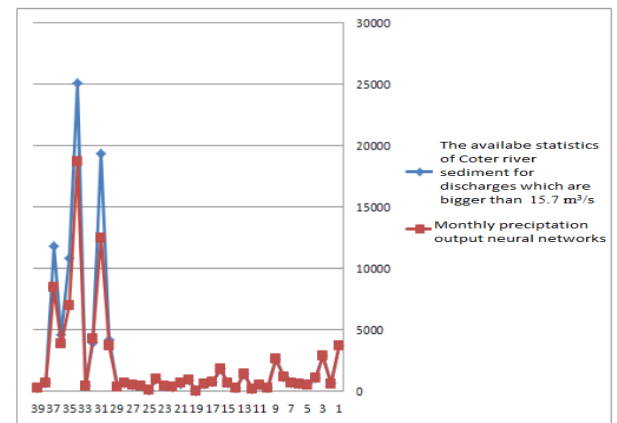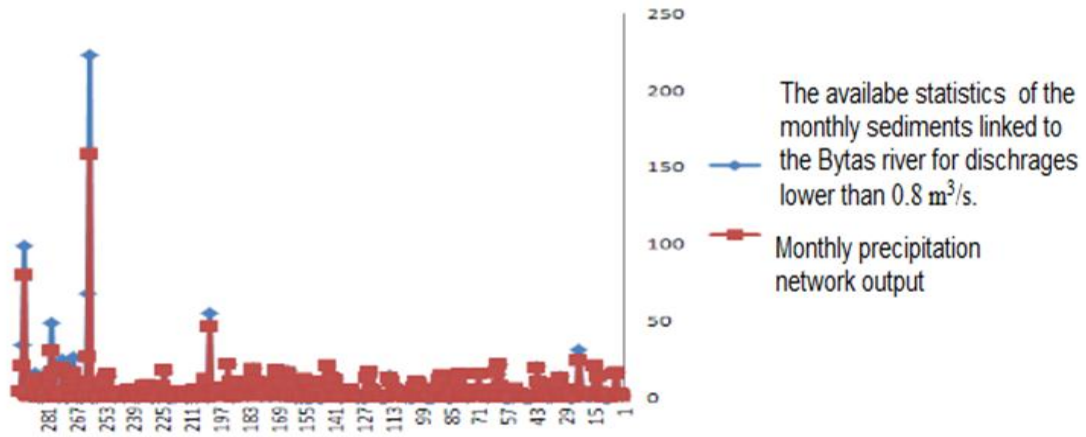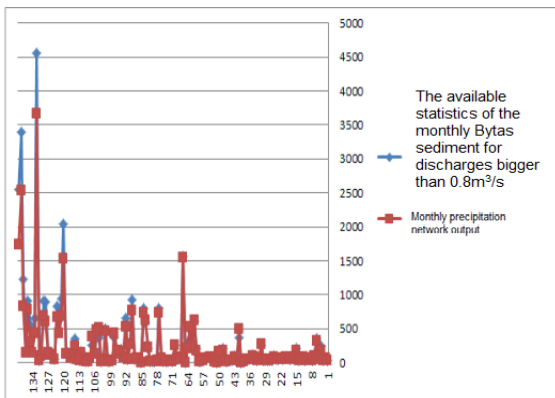
	Number of hidden layers	Transfer for hidden layer	Transfer for output layer	Learning rule	R (Training)	MSE (Training)	R (Test)	MSE (Test)
Cawter with low discharge rate	3	Sigmoid Axon	Linear Axon	Levenberg Marquardt	0.865	0.0121	0.827	0.038
Cawter with high discharge rate	1	Sigmoid Axon	Linear Axon	Levenberg Marquardt	0.892	0.0101	0.809	0.037

Table 2. The result of the artificial neural network in estimating the sediments of the Mahabad dam over test and training phases related to the Baitas River.

	Number of hidden layers	Transfer for hidden layer	Transfer for output layer	Learning rule	R (Training)	MSE (Training)	R (Test)	MSE (Test)
Baitas with low discharge rate	2	Sigmoid Axon	Linear Axon	Levenberg Marquardt	0.833	0.0141	0.715	0.0540
Baitas with high discharge rate	1	Sigmoid Axon	Linear Axon	Levenberg Marquardt	0.911	0.0089	0.0857	0.037

Figure 5. The performance of the neural network in estimating sediment amount within the Mahabad dam reservoir from the Baitas River for discharges lower than 0.8 m³/s

Figure 6. Performance of the neural network in estimating the amount of sediments from The Baitas for discharges with a value bigger than 0.8 m³/s.

Figures 4 and 5 represent the results of this method in comparison with the real data related to the sediment. By investigating the above figures and data it can be inferred that the designed network for the Baitas and Cawter which is based on this approach, is more efficient. However, as it is obvious in the shapes, the network estimation of the sediments with lower discharges due to the higher samples and following trainings is more precise and reliable. Of course, the lack of accurate data recorded during the flood, the availability of the fewer data and the existing paradox among the input and output data is not ignorable.

The results of hydrometer approach

The best method of investigating sediment discharge in a hydrometric manner can be done via curve approach (SRC). The curve method includes a graph or equitation which represents the relation between discharge and sediment. In order to estimate the sediment load by the use of measured discharges, this method is tried.

In this study, the result of a long term estimation of suspended load linked to The Mahabad Chay at Baitas and Cawter station are used within the curve approach.

A: Cawter

$$Q_s = 6.522 Q_w^{1.181}, Q_w < 15.7 \qquad (5)$$
$$Q_s = 0.1 Q_w^{2.7}, \ Q_w \geq 15.7 \qquad (6)$$

B: Bytas
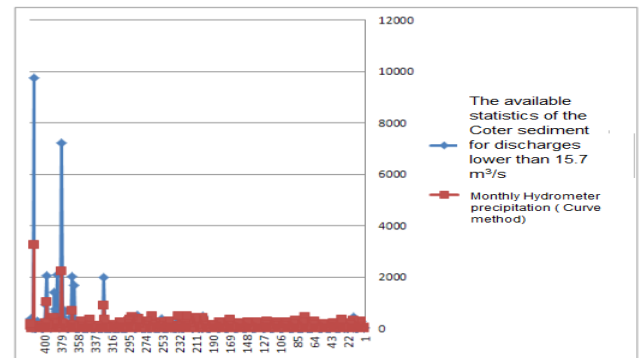
$$Q_s = 5.53 Q_w^{1.0704}, Q_w < 0.8 \qquad (7)$$
$$Q_s = 6.96 Q_w^{2.1847}, 0.8 \leq Q_w \leq 19.47 \qquad (8)$$
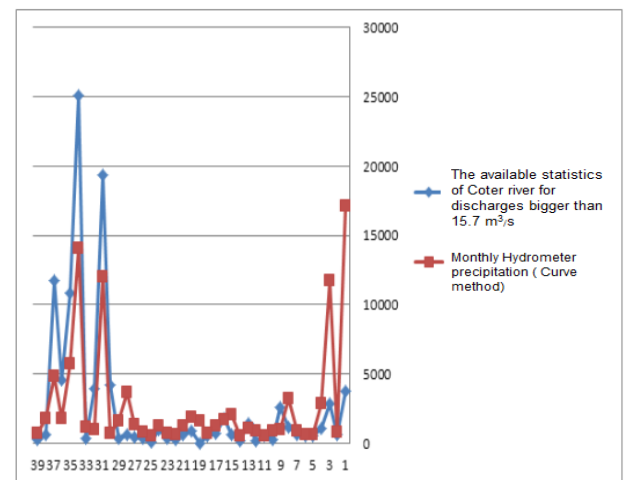$$Q_s = 89.35 Q_w^{1.325}, Q_w > 19.47 \qquad (9)$$

In the above equations, Q_s and Q_w refer to sediment discharge at ton/day and water discharge at m³/s respectively. It is worth to say that the Sediment concentration is relatively large range which is depended on different factors like irrigation, measurement season, Accuracy of measurement and the origin of swashes.

Table 3. The result of Hydrometer approach in estimation of the reservoir sediment from the Cawter

	Power relation	**r**
The Cawter with low discharge	$Q_s = 6.522 Q_w^{1.181}$	0.4145
The Cawter with high discharge	$Q_s = 0.1 Q_w^{2.7}$	0.454

Figure 7. The performance of the Hydrometer approach in estimating the sediment of the Mahabad dam reservoir from the Cawter location for discharges lower than 15.7 m³/s.
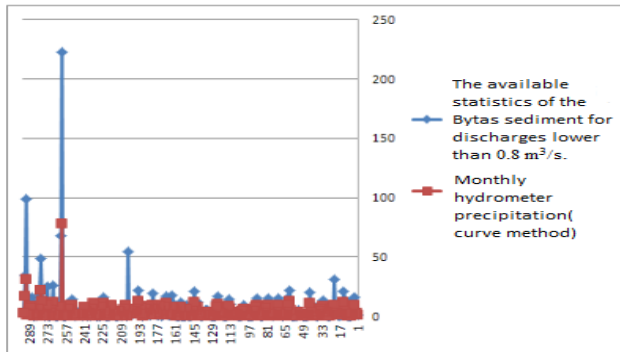

Figure 8. The performance of the Hydrometer approach in estimating the sediment of the Mahabad dam reservoir from the Cawter location for discharges bigger than 15.7 m³/s.
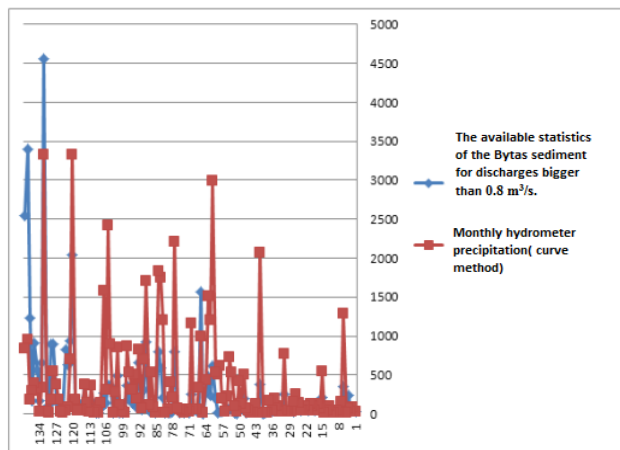
The r variable can be calculated for the Bytas, for both high and low discharges. Table 4 and figures 8 and 9 shows the result of the Hydrometer model in comparison with the available sediments statistics.

Table 4. The results of the Hydrometer approach in estimating sediment of the Mahabad dam reservoir from the Baitas River location

	Power relation	r
Baitas with low discharge	$Q_s = 5.53 Q_w^{1.0704}$	0.576
Baitas with high discharge	$Q_s = 6.96 Q_w^{2.1847}$	0.654

Figure 9. The performance of the Hydrometer approach in estimating sediment of the Mahabad dam reservoir from the Baitas location for discharges lower than 0.8 m³/s.

Figure 10. The performance of the Hydrometer approach in estimating sediment of the Mahabad dam reservoir from the Baitas location for discharges bigger than 0.8 m³/s.

By observing the mentioned statistics and figures it can be deduced that hydrometer approach is not so effective in controlling the conditions of the Baitas and Cawter for various discharges. Of course, the lack of accurate data recorded during the flood, the availability of the fewer data and the existing paradox among the input and output data is not ignorable. The results of this calculations state that the neural network approach is stronger and more efficient than routine hydrometer approaches like curve method. The neural network is somehow smart and it can create any demanded network depended on the problem itself. The correlation coefficient and the average square error are two prominent factors that have adjusted the elements of the network that when network errors reach its limit, the network system automatically halts. This automatic reaction of the system is done by training system the probability of the errors and by giving much more weight to the groups which are many in number. If the curve approach were used, the results would be less reliable and we would conclude that this kind of method is unable in estimating the sediment amount in the dam reservoir.

CONCLUSION

1. The comparison results after investigating transportation and movement functions pointed out that between eight Axon collections, nonlinear sigmoid Axon within the interface layer were a more efficient function in estimating the amount of Mahabad dam's sediment. Moreover, Lunberg-Markuet Training algorithm using less training cycles and has fewer errors is used as the base algorithm for network learning phase.

2. By investigating the neural network results at the Cawter station over training and test phase, for discharges higher and lower than 15.7 m³/s, it can be concluded that this approach is more efficient than hydrometer approach even with the same discharges divisions. So that the correlation coefficient is 0.892-0.809 and 0.865-0.827 for low and high discharges, respectively and these results is much more acceptable and realistic if they compare with the ones related to the hydrometer which are 0.454 and 0.414 for high and low discharges, respectively.

3. By investigating the neural network results at the Baitas station over training and test phase, for discharges higher and lower than 0.8 m³/s, it can be concluded that this approach is more efficient than hydrometer approach even with the same discharges divisions. So that the correlation coefficient 0.911-0.854 and 0.833-0.715 for high and low discharges, respectively and these results is much more acceptable and realistic if they compare with the ones related to the hydrometer which are 0.454 and 0.414 for high and low discharges respectively.

By investigating the above figures and data it can be inferred that the designed network for the Baitas and Cawter which is based on this approach, is more efficient. However, as it is obvious in the shapes, the network estimation of the sediments with lower discharges due to the higher samples and following trainings is more precise and reliable. Of course, the lack of accurate data recorded during the flood, the availability of the fewer data and the existing paradox among the input and output data is not ignorable.

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