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Evaluation of Artificial Intelligent Methods to Release Sediments from Reservoirs by Pressurized Flushing

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ABSTRACT

Sedimentation in reservoirs is an important issue that should be considered for the reservoirs operation and useful life. In this study, application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN) in prediction of the sediment release from the bottom outlet using semi-cylinder for different variables was evaluated. Dimensionless parameters such as dimensionless length and height of the gap and water level were considered. The results indicated that both ANFIS and ANN had an acceptable performance in this matter. The best performance of the ANFIS and ANN models had root mean square errors equal to 3.95×10^{-5} and 4.34×10^{-5}, respectively.

Keywords

Artificial Neural Network, Neuro-fuzzy, Pressurized flushing, Semi-Cylinder.

1. Introduction

Sedimentation is one of the important issues that should be considered in useful life and operation of the reservoirs. In natural rivers, the amount of input and output sediments in a time interval is in balance. However, this sediment balance is lost by construction of the dams in river paths and the flow velocity in rivers is reduced so that the reservoirs act as sediment traps. Sediment flushing is necessary to maintain the long-term storage in reservoirs. If sediment washing is done correctly, the necessity of building new dams is decreased and additional costs could be avoided. In reservoirs, flushing can be classified into pressurized and free flow flushing or draw-down. During pressurized flushing, water is released through the bottom outlets while the water level in the reservoir is kept above the outlet. In pressurized flushing, a very limited area in the reservoir is cleared from sediments.

In recent years, artificial intelligent methods have been widely used for prediction purposes in many fields. Realizing the nonlinear behavior of the systems and phenomenon is the most important advantage of these methods. This is why they are mostly applied to models in which there is not exact knowledge about their behavior. Construction of the physical models is costly and time consuming, so artificial intelligent methods could be a good choice in hydraulic model analysis. Neural networks, Neuro-fuzzy systems and genetic programming methods are some of the most important artificial intelligent methods, but limited studies have been done in hydraulic model analysis using

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these methods. Some of studies in this field are mentioned in the following paragraph.

ANNs have been reported to provide reasonably good solutions for hydraulic engineering problems, particularly for cases of highly nonlinear and complex relationship among the input-output pairs in corresponding data (Guven and Gunal, 2008, Azamathulla et al., 2010, Azamathulla and Ghani, 2010). Chang and Chang (2001) used the ANFIS to predict the water level in reservoirs. An integrated stage–discharge–sediment concentration relation for two sites on the Mississippi River in the United States was studied by Jain (2001) using ANN. Liriano and Day (2001) predicted depths of scour at culvert outlets. Kambekar and Deo (2003) estimated the scour geometry around groups of piles in the ocean. Azinfar et al. (2004) applied the ANN to forecast scour depths at the sluice gate. ANFIS was employed by Kazeminezhad et al. (2005) and Mahjoobi et al. (2008) to predict wave characteristics. Sediment concentration was predicted by Kisi [2005] using ANFIS. Tayfur and Guldal (2006) used ANN to estimate total daily suspended sediments in natural rivers. Estimation of scour around hydraulic structures was done by Azamathulla et al. (2008) using artificial neural networks and ANFIS. ANNs have prediction, flow/pollution simulation, and parameter identification features (ASCE Task Committee, 2000). ANN has also been used for designing the time-varying groundwater remediation by Chu and Chang (2009). Evaluation of total sediment load formulae was done by Yang et al. (2009) using ANN. Analysis of the lateral outflow over the rectangular-side weirs located on a straight channel was conducted by Bilhan et al. (2010) using two different neural networks. Cigizoglu (2010) used ANN approach to predict suspended sediment concentrations in northern England. He applied discharge and sediment concentration parameters in his study. Application of the soft computing approaches of ANN-RBF and ANFIS to predict the local scour depth at culvert outlets was described by Azamathulla et al. (2011).

The objective of this study is to develop an improved predictive model for estimation of the scour depth using ANFIS and ANN methods. Dimensionless parameters such as dimensionless length and height of the gap and water level were considered. In order to compare the results, simulations were done using both ANFIS and ANN methods. The acceptable results of ANFIS and ANN systems are also demonstrated.

2. Modeling and Analysis of the Methods

2.1. Experimental Model

Experiments were conducted at the Hydraulic Laboratory of Water Engineering Department, University of Tabriz. The physical experiments were carried out in a rectangular cube-shaped reservoir. The reservoir has a length of 120 cm, a width of 100 cm and a height of 85 cm. Sediments were filled up to the lower edge of the valve located 28 cm above the bottom of the model. The bottom outlet of the basin was a circular orifice (sluice gate) of a 5.08 cm (2 inch) diameter and a gate valve as the discharge regulator (Fig. 1). After passing the lower outlet, sediments entered the sedimentation basin. The flow returned from the sedimentation basin to the main reservoir and the volumetric flow discharge was measured. Non-cohesive sediments with a median sediment diameter of 0.51 mm and a density of 1700 kg/m3 were used. For each model, experiments were conducted for three water levels of 15, 30 and 50 cm with a constant flow discharge of 2 lit/s. AS Semi-Cylindrical structure was applied in front of the bottom outlet to create and reinforce the vortex flow. By placing this structure, the vortex flow was created and more sediments were discharged from the front part of the bottom outlet. A gap was created under the Semi-Cylinder to create the vortex flow. At first, experiments were conducted for Semi-Cylinders with diameters of 12.7 and 15.24 cm and gaps of different arc lengths (L_a) and constant height (H_a) on the Semi-Cylinders. The optimal arc length was obtained for which the maximum sediment discharge occurred. In optimal arc length, the height of the gaps was changed in such a way that in each experiment, the top of the gap was in the same level of the accumulated sediments. After finding a suitable height and arc length, experiments were conducted for Semi-Cylinders with diameters of 5.08, 7.62, 10.16, 12.7, 15.24, 20.82 and 25.4 cm. A total of 93 experiments were performed for all of the models for 3 different water levels. The experimental setup and location of the Semi-cylinder structure are illustrated in Fig. 2.

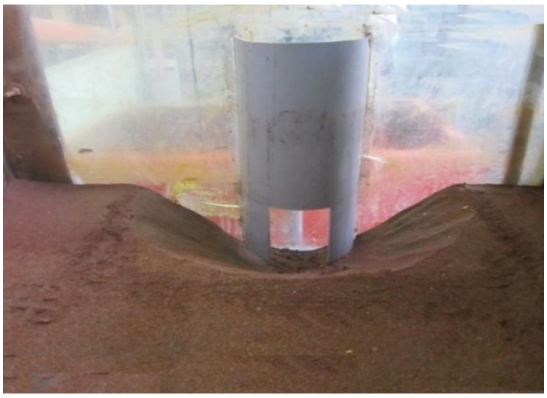


Fig. 1. Experimental setup

Fig. 2. Location of the Semi-cylinder structure in front of the outlet.

2.2. Theory and Dimensional Analysis

By opening the valve, the flushing cone is formed in front of the gate. Sediment discharge (*Qs*) is a function of different parameters including water level in the reservoir (H_w), acceleration due to gravity (*g*), density of the deposited sediments (ρ_s), water density (ρ_w), sediments median diameter (d_{50}), diameter of the bottom outlet (*D*), dynamic viscosity of the fluid (μ), diameter of the Semi-Cylinder structure (D_a), gap height at the bottom of the Semi-cylinder (*Ha*) and gap length on the Semi-cylinder (L_a). It can be written as:

$$f_1(Q_s, H_w, g, \rho_s, \rho_w, d_{50}, D, \mu, D_a, H_a, L_a) = 0 \qquad (1)$$

Using the Buckingham π theorem, Eq. (1) may be written as:

$$f_2\left(\frac{H_w}{D}, \frac{\rho_s}{\rho_w}, \frac{d_{50}}{D}, \frac{Q_s}{D^{2.5}g^{0.5}}, \frac{\mu}{\rho_w g^{0.5} D^{1.5}}, \frac{L_a}{D}, \frac{H_a}{D}, \frac{D_a}{D}\right) = 0 \qquad (2)$$

Since ρ_s, ρ_w, d_{50} and D were constant in all the experiments and parameter $\frac{\mu}{\rho_w g^{0.5} D^{1.5}}$ represents the effect of the viscosity (Reynolds number was about 35000), so the effect of these parameters can be neglected and Eq. (2) can be rewritten as:

$$f_3\left(\frac{H_w}{D}, \frac{Q_s}{D^{2.5}g^{0.5}}, \frac{L_a}{D}, \frac{H_a}{D}, \frac{D_a}{D}\right) = 0 \qquad (3)$$

Ranges of the experimental dimensionless parameters are shown in Table 1.

Table 1. Experimental dimensionless parameters

Dimensionless parameters	$Qs/D^{2.5}g^{0.5}\times 10^5$	H_a/D	L_a/D	H_w/D
Range of variations	2.38-100.11	0.25-3	0.5-3	2.95-9.84

2.3. Neural Networks

The neural network is a tool for data modeling in which the structure is inspired by human brain biological networks. These networks are able to learn from examples and generalize and this is one of the similarities of these networks to human brain. In addition, their ability to represent both linear and nonlinear relationships is one of the advantages of these networks. The Classification, Prediction and noise reduction are some of the important applications of these networks. Neural networks are composed of many neurons that co-operate to perform the desired function. The output of a neuron is a function of the weighted sum of the inputs plus a bias. The function of the entire neural network is simply the computation of the outputs of all the neurons. The measured data are used to train the neural networks. By processing the measured input and output data, neural networks learn the general rules. By applying new inputs, the network analyzes data and generates outputs according to the pre-generated rules.

One of the most common networks is the Multi-Layer Perceptron. In these networks, unsupervised learning method is used to train the network. These networks contain input, output and hidden layers. The outputs of one layer act as inputs to the next layer. The structure of a MLP network is illustrated in Fig. 3.

As shown in Fig. 3, inputs that are fed into the input layer are multiplied by weights and entered to the hidden layer. They are summed and processed by an activation function. The outputs of a hidden layer enter the next one. Finally, the data leaves the last hidden layer and is applied to the output layer to produce the network output. One of the common methods for network training is back propagation that is a supervised training method. The algorithm of this method is based on minimizing the error of the network using derivatives of the error function.

A 3-layer MLP network with back propagation training method was used in this paper. In the proposed method, sensitivity analysis of the model is based on the number of the hidden layer neurons and application of different transfer functions to different input variables. Seventy percent of the experimental data was used for network training and the remaining 30% of the experimental data was used for testing the network. A program code, including neural network toolbox was written in MATLAB language for ANN simulation.

2.4. Adaptive Neuro-Fuzzy Inference System (ANFIS)

Jang (1993) presented a learning procedure for the fuzzy inference system (FIS) that uses an ANN learning algorithm for constructing a set of fuzzy if-then rules with appropriate membership functions (MFs) from specified input-output pairs. A basic structure of ANFIS is illustrated in Fig. 4.

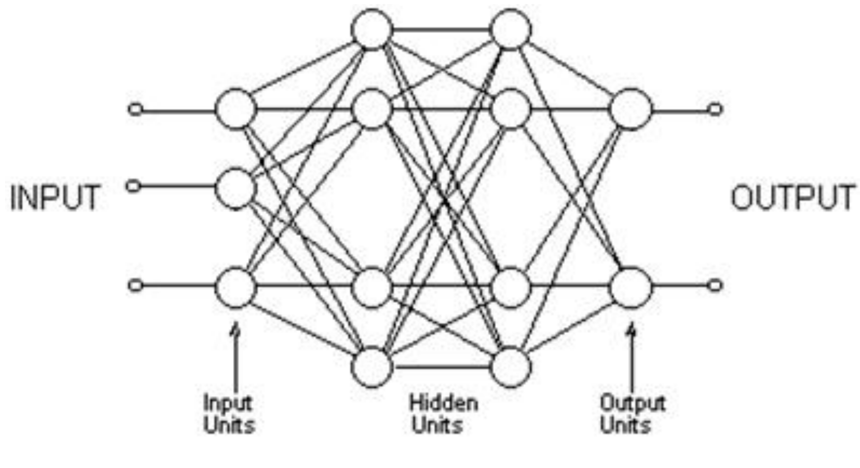


Fig. 3. Structure of a MLP network (Kisi et al., 2009)

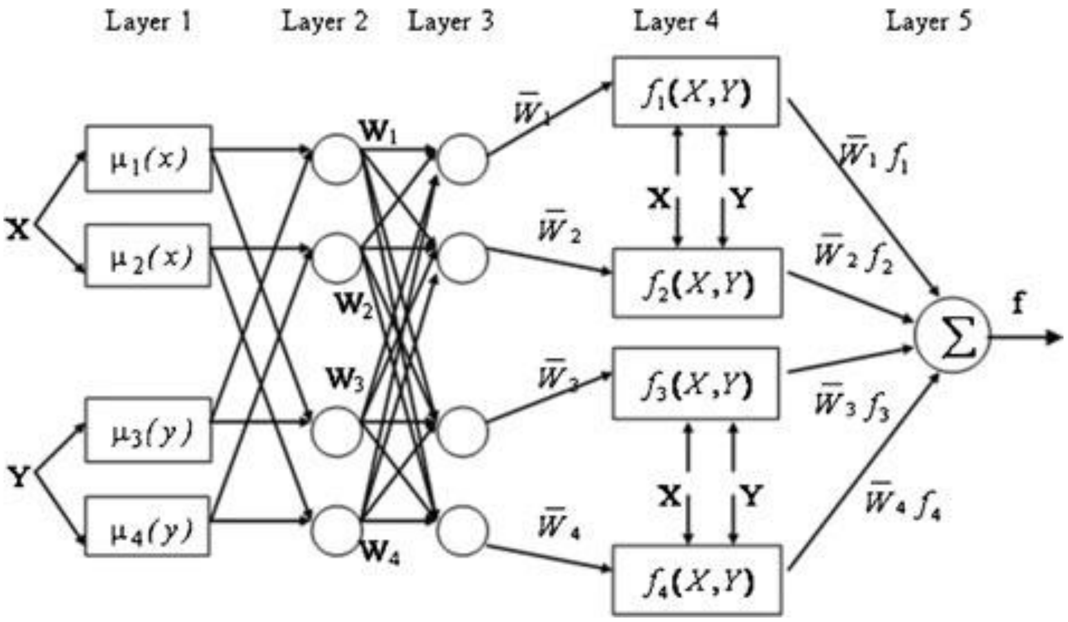


Fig. 4. Basic structure of the ANFIS (Kisi et al. 2009)

To build up a fuzzy system, the linguistic variables should be first provided in addition to the numerical variables. Then, the system requires If/Then fuzzy rules to qualify simple relationships between the fuzzy variables. A typical rule set with two fuzzy If/Then rules in a first-order Sugeno system can be shown as follows:

Rule 1: If x is A1 and y is B1, then $f_1=p_1x+q_1y+r_1$ (4)

Rule 2: If x is A2 and y is B2, then $f_2=p_2x+q_2y+r_2$ (5)

where *x* and *y* refer to the input and output variables, respectively, *A* and *B* terms denote the linguistic terms of the precondition part with MF. If part of the rule, 'x is A', is called the premise, while then part of the rule, 'y is B', is called the consequent and *p*, *q* and *r* indicate the consequent parameters (Sayed et al., 2003). A detailed description of ANFIS can be found in Jang (1993).

Similar to ANN, 70% of the whole data set was applied to train the ANFIS system. Also 30% of the data was used to test the system. A program code including the fuzzy toolbox was written in MATLAB for ANFIS simulation.

2.5. Model Evaluation Indexes

To evaluate the Neuro-fuzzy system results, the coefficient of determination (R^2) and root mean square error (RMSE) indexes were used as follows:

$$R^2 = \left(\frac{\sum xy}{\sqrt{\sum x^2}\sqrt{\sum y^2}} \right)^2 \quad (6)$$

$$RMSE = \left[\frac{\sum (x-y)^2}{n} \right]^{1/2} \quad (7)$$

where *x* and *y* indicate dimensionless amounts of the experimental sediment discharge and the predicted sediment discharge by the model, respectively.

3. Results and Discussion

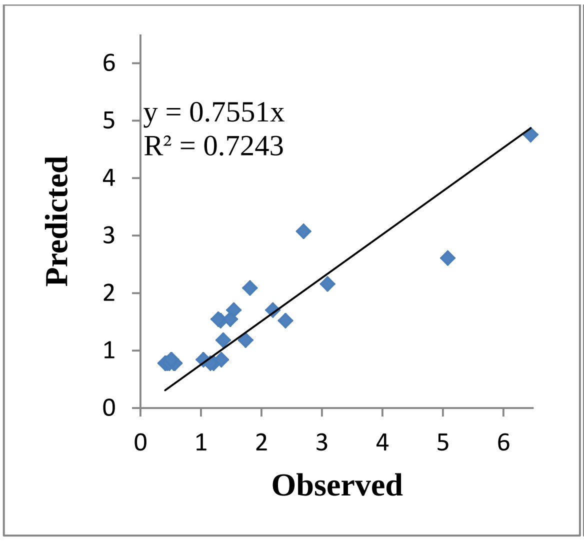
The structure and error of Neuro-fuzzy model for different input patterns in predicting the dimensionless sediment discharge are shown in Table 2.

Table 2. Structure and error indexes in Neuro-fuzzy model for different patterns of inputs in test period

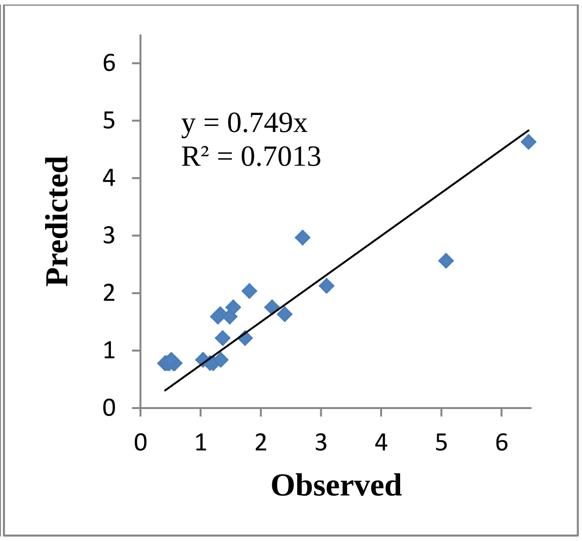
Pattern number	Input pattern	Membership function	Number of membership functions	R^2	RMSE (10^{-5})
1	H_a/D	Triangular	2	0.84	7.20
2	H_a/D, L_a/D	Triangular	2,2	0.85	6.98
3	H_a/D, L_a/D, H_w/D	Triangular	2,2,3	0.94	95

From Table 2 it can be seen that pattern 3 has the minimum prediction error in which all of the input variables are considered in sediment discharge prediction. In this case, R^2 and RMSE were 0.94 and 3.95×10^{-5}, respectively.

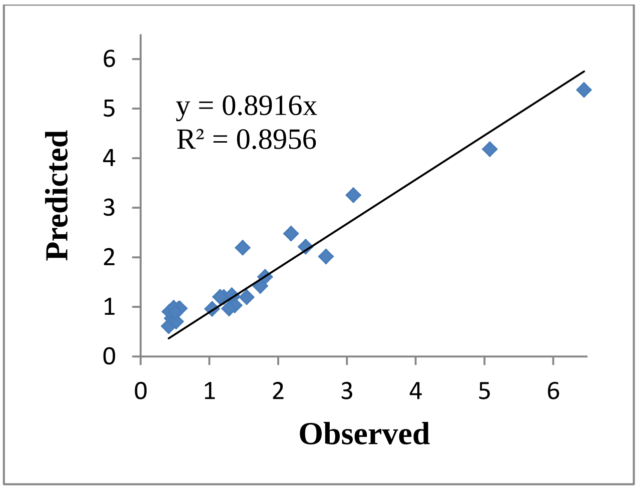
To find an optimal structure for the Neuro-fuzzy system for a specific pattern, different membership functions such as triangular and Gaussian functions were applied. The results showed that for triangular membership functions, RMSE has the minimum value and this membership was selected as the optimal structure for the system. In pattern 3, the optimal structure has 2 members for variables H_a/D and L_a/D, and 3 members for variable H_w/D. The results of ANFIS prediction for different input patterns of dimensionless sediment discharge are illustrated in Fig. 5.



(a) pattern 1



(b) pattern 2



(c) pattern 3

Fig. 5. Observed versus predicted sediment discharges for different patterns using ANFIS: (a) pattern 1, (b) pattern 2, and (c) pattern 3.

As shown in Table 2 and Fig. 5, by adding the dimensionless parameter of L_a/D to the model (pattern 2), model performance became better considering the error indexes but with Subtle changes. Addition of the H_w/D parameter (pattern 3) improved the Neuro-fuzzy system performance in predicting the sediment discharge. In addition, the values of R^2 and RMSE improved by 10% and 43%, respectively, with respect to pattern 2.

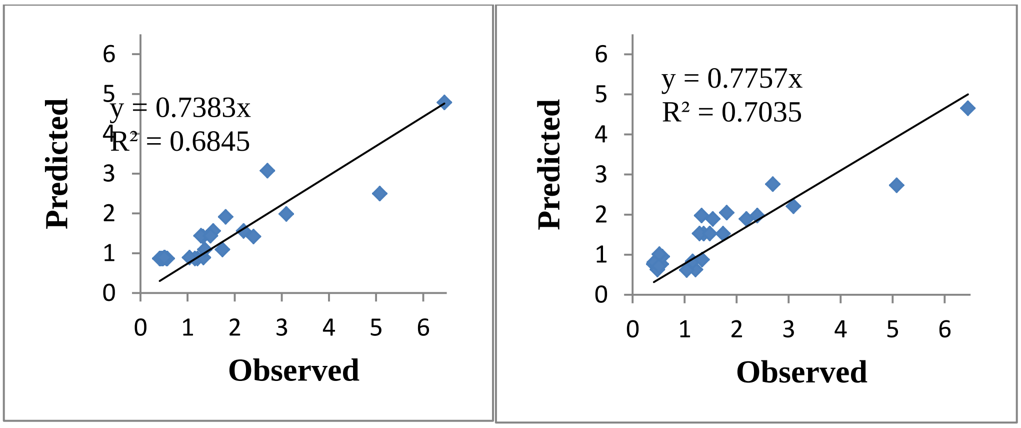
The optimal structure and error indexes of the neural network model for different input patterns in predicting the dimensionless sediment discharge are shown in Table 3. Like ANFIS, pattern 3 was the best pattern for the neural network model. Performance indexes of R^2 and RMSE obtained for the test period were 0.94 and 4.34×10^{-5}, respectively. In the neural network, the optimal model was obtained by changing the activation functions and number of the hidden layer neurons. For all the patterns, the log-sigmoid and linear functions were considered as the best activation functions between input-hidden layer and hidden-output layer, respectively. 250 epochs were used to train the network. The optimal number of neurons in hidden layer for different patterns is shown in Table 3. As shown in this table, the number of the neurons for the best pattern (pattern 3) is 6. The results showed that by using pattern 1, which contains only the dimensionless parameter H_a/D, acceptable results were obtained. By adding L_a/D and H_w/D parameters to the model, the performance of the system significantly improved.

Fig. 5 illustrates the distribution diagram of the dimensionless sediment discharge for the observed data and data obtained by simulation with ANN for different input patterns. The results of these diagrams were in full agreement with the results presented in Fig. 5.

By comparing the results rpresented in Tables 2 and 3 and Figs. 5 and 6 it can be concluded that the Neuro-fuzzy model showed a better performance than the neural network model considering the error indexes for different patterns. Considering R^2, both models showed almost the same performances but considering RMSE, the error decreased by 9% in the Neuro-fuzzy model.

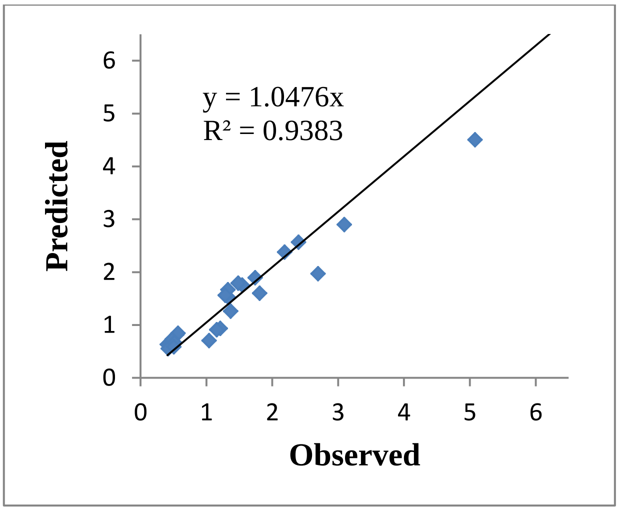
Table 3. Structure and error indexes of the neural network model for different patterns of inputs in test period

RMSE (10^{-5})	R^2	Number of neurons in hidden layer	Input pattern	Pattern number
7.56	0.82	1	Ha/D	1
7.33	0.84	4	Ha/D, La/D	2
4.34	0.94	6	Ha/D, La/D, Hw/D	3



(a) Pattern 1 (b) Pattern 2

Fig. 6. Observed versus predicted sediment discharges for different patterns using ANNs: (a) pattern 1, (b) pattern 2, and (c) pattern 3.



(c) Pattern 3

Fig. 6. Continued.

4. Conclusions

In this paper, performance of the Neuro-fuzzy system in prediction of the dimensionless sediment discharge was evaluated and results were compared with the neural network model results. Different input patterns including dimensionless parameters such as height and length of the Semi-cylinder and water depth were used to predict dimensionless sediment discharge. For both models, pattern 3 that contained all of the Hydraulic parameters showed the best performance. In this pattern, R^2 and RMSE indexes for Neuro-fuzzy model were 0.94 and 3.95×10^{-5}, respectively and for neural network model were 0.94 and 4.34×10^{-5}, respectively. By comparing the results of the Neuro-fuzzy and neural network models it can be concluded that the Neuro-fuzzy model is a better one in prediction of the dimensionless sediment discharge by which the RMSE index decreased by 9%.

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