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Estimating river suspended sediment yield using MLP neural network in arid and semi-arid basins Case study: Bar River, Neyshaboor, Iran

H. Memarian Khalilabad[a*], S. Feiznia[b], K. Zakikhani[c]

[a] *Expert of Abkhizgostar-e-Shargh Consulting Engineers Co., Mashhad, Iran*
[b] *Professor, Faculty of Natural Resources, University of Tehran, Karaj, Iran*
[c] *Student, College of Civil Engineering, University of Tehran, Tehran, Iran*

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Abstract

Erosion and sedimentation are the most complicated problems in hydrodynamic which are very important in water-related projects of arid and semi-arid basins. For this reason, the presence of suitable methods for good estimation of suspended sediment load of rivers is very valuable. Solving hydrodynamic equations related to these phenomenons and access to a mathematical-conceptual model is very difficult and in most cases, necessary data for these models are not available. On the other hand, most of the widely-used experimental methods are not accurate-enough. The principles of wise method are: using the hidden knowledge in the data; effort to extract intrinsic relations between data; and generalizing them to other situations. Artificial neural network is one of the most important methods of artificial intelligence in which by inspiring from the model of human brain while performing training process, data-related information are stored into weights of network. The aim of this research is using MLP (Multi-Layer Perceptron) neural network to obtain sediment rating curve. After entering input patterns into the network and defining a neuron for input and a neuron for output layers and performing repeated trial and error, optimum architecture (topology) of MLP network was defined as a network with 5 neuron for hidden layers and Hyperbolic tangent activation function for the first and second hidden layers and Linear function for the third hidden layer.

Keywords: Arid and semi-arid basins; suspended sediment yield; MLP neural network; Perceptron

1. Introduction

Accurate estimating the sediment yield is very important in water-related projects. Sedimentating in dam reservoirs and declining their useful volume, river avulsion due to channel sedimentation, decreasing in the water transmission capacity of water installations and quality degradation of drinking and agricultural water are some problems of water projects especially in arid areas.

There are two different ways to estimate suspended sediment yield of rivers. The first method is using mathematical models in which they are focused on physical concepts and hydrodynamic and flow-field equations that should be solved. These models usually need various data such as material gradation, water temperature, specific weight and viscosity, flow velocity, river profile, the kind of materials in the sides of channel and river slope. In most cases such data are not available and the most available ones include the water and sediment discharges. The second approach is preparing sediment rating curves on water and sediment discharge data. The most common way is fitting a power curve with the form of $Q_s=a.Q_w^b$ in which Q_s is sediment discharge, Q_w is water discharge and a, b are constant coefficients (Montazer et al., 2003).

For using the artificial neural network in estimating the river sediment yield, some

[*] Corresponding author. Tel.: +98 261 2223044;
Fax: +98 261 2227765.
E-mail address: hadi_memarian@yahoo.com

researches have been done recently. Kumorjain (2001) estimated suspended sediment yield of Mississippi river by this method. Using continuous data set of water-level, water and sediment discharges, sediment concentration in each time step has been calculated as a function of water level and water discharge of that time step and previous time step. Although the results indicated optimum operation of multi-layer perceptron neural network, but this method is not applicable when a continuous series of water discharge and sediment concentration are not available (Kumorjain, 2001). In another research that has been done on water and sediment discharges of Jajrood River, Iran, the results obtained from MLP neural network have been reported to be satisfactory (Avarideh et al., 2002).

Montazer et al. (2003) estimated sediment yield of Bazoft River, Iran, using artificial neural network. They used two kinds of neural network: Multi-layer perceptron neural network and counter propagation of Grassberg and stated that the Grassberg network, before mapping, classified the patterns and created non-liner mapping for each class. The result was accurate mapping but not necessarily an ascending one. Therefore, due to the fact that sediment rating curve is usually an ascending one, this kind of neural network is not suitable. Despite of counter propagation of Grassberg network, multi-layer perceptron network produces ascending mapping which with sigmoid function in the first hidden layer and linear function in the second hidden and output layers, is able to do better estimation of high sediment discharges and can be used in sediment rating curve preparation. Meanwhile they considered the effect of mean monthly air temperature on their research and concluded that this parameter does not have a considerable effect on improvement of the model (Montazer et al., 2003).

Ghodsian and Zaker Moshfegh (2003) investigated application of MLP neural network on hydraulic parameters of side sluice gates. They also concluded that the network with hyperbolic tangent activation function for hidden layer and linear function for output layer operates better than network with hyperbolic tangent function for all layers (Ghodsian et al., 2003).

Najafi Hajivar et al. (2008) investigated the ability of artificial neural network and regressional functions for estimating suspended load of rivers in the Sira station in Iran. The results of this research showed the better efficiency of artificial neural network in the summer and autumn seasons than regressional functions.

Yazdani et al. (2008) studied the quality condition of Zayanderood River by a Multi-layer Perceptron Network and selected the best network, a network with a hidden layer, with regarding the amount of network error.

In the present article, sediment yield of Bar River at Ariyeh hydrometric station has been estimated by MLP neural network and the effect of sigmoid threshold function and hyperbolic tangent in model operation have been evaluated.

2. Materials and methods

2.1. Multi-layer Perceptron Network (MLP)

Perceptron model was first presented by Rosenblatt (10) and was then modified by Rumelhart and McClelland as multi-layer perceptron (MLP). This network consists of one input layer, one or several hidden layers and one output layer. General structure of this network is shown in fig.1. Conformity of neural network with biological neuron is shown in figure 2. The most important threshold functions used for neurons are: linear function, hyperbolic tangent and sigmoid which are shown in figure 3.

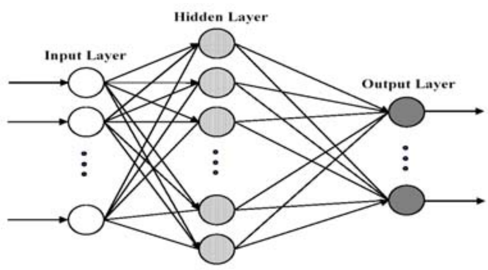

Fig. 1. General structure of MLP network (2)

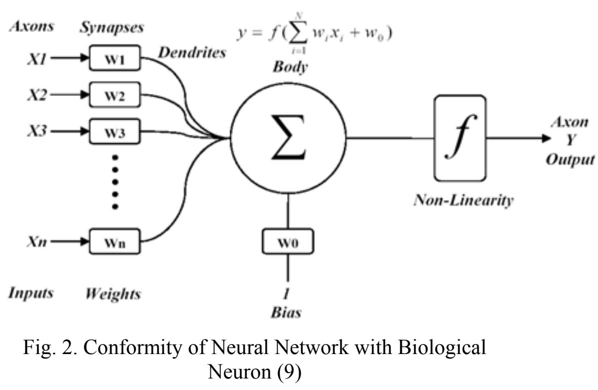

Fig. 2. Conformity of Neural Network with Biological Neuron (9)

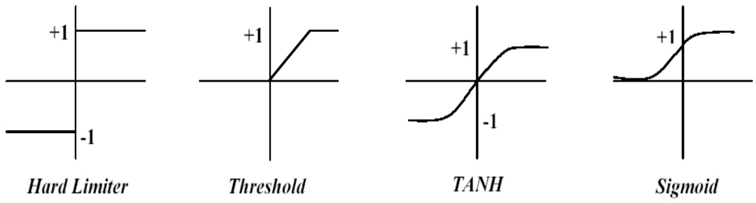

Fig. 3. The most important functions for activation of neurons (3)

2.2. Back Error propagation Algorithm

For multi-layer perceptron network training, back error propagation learning is used. Good behavior always deserves encouragement and bad behavior deserves punishment.

In back error propagation method, this general rule is followed. In this method, input pattern is first presented to network and output is then calculated. The error in output layer is calculated by comparing calculated output by the network and favorite (goal) output. This error is backing diffused from each layer to the previous layer. Changes in weighs are related to the amount of this error (Ghodsian et al., 2003). In many cases sigmoid function is used as activation function. The procedure is as follows:

$$O_{j,m}=Sig(Net_{j,m})=\frac{1}{1+e^{-Net_{j,m}}} \quad (1)$$

$$f'(Net_{j,m})=O_{j,m}(1-O_{j,m}) \quad (2)$$

$$Net_{j,m}=\sum_{i}^{n_{m-1}} W_{ji,m}.O_{i,m-1}+b_{j,m} \quad (3)$$

Sometimes hyperbolic tangent function is used as activation function. In this research this function is also used as follows:

$$O_{j,m}=TANH(Net_{j,m})=\frac{e^{Net_{j,m}}-e^{-Net_{j,m}}}{e^{Net_{j,m}}+e^{-Net_{j,m}}} \quad (4)$$

In these equations, $w_{ji,m}$ is weight coefficients between i neuron on m-1 layer with j neuron of m layer in n epoch or repeat, $o_{j,m}$ is output of j neuron on m layer, n_m is number of neurons in m layer and b is bias term that is similar to regression model fixed term. In the last layer, predicted output is compared with the real output or goal and then sum of square error (SSE) or root mean square error (RMSE) is calculated for the last layer as follows:

$$SSE=\sum_{p}\sum_{j=1}^{n}(t_{pj}+o_{pj}) \quad (5)$$

$$RMSE=\sqrt{\frac{\sum_{p}\sum_{j}(t_{pj}-o_{pj})^2}{n_p.n_o}} \quad (6)$$

In this equation, t_{pj} is the jth real output element related to P pattern, O_{pj} is jth calculated output element related to P pattern (predicted by network), n_p is number of pattern and n_o is number of neurons on the last layer (2).

It is necessary to mention that bias is an additional node with fixed output (usually one) added to input and hidden layers and it allows us to move the origin of defined spatial cloud by input variables (Omid, 2002).

2.3. Training Algorithm

Back error propagation algorithm processes are as follows:

1. Assigning small random weight to each connection.
2. Adopting input pattern for network and calculating output on the last layer as follows:

$$Net_{j,m}=\sum_{i=1}^{n_{m-1}}W_{ji,m}.O_{i,m-1}+b_{j,m} \quad (7)$$

$$O_{j,m}=f(Net_{j,m}) \quad (8)$$

3. Calculating network error using equations (5) and (6) and evaluation of necessity for algorithm continuation and/or terminating the training process.
4. For m=L, m=L-1, m=1 layers:
4-1. Calculating error related to each neuron:
For output layer neuron:

$$S_{j,m}=f'(Net_{j,m}).(t_j-O_{j,m}) \quad (9)$$

For hidden layer neuron:

$$S_{j,m}=f'(Net_{j,m}).\sum_{k=1}^{n_{m+1}}W_{kj,m+1}.\delta_{k,m+1} \quad (10)$$

$W_{kj,m+1}$ is coefficient of weight between j neuron on m layer and k neuron on m+1 layer

on n repeat (epoch) and $\delta_{k,m+1}$ is K neuron error on m+1 layer.
4-2. Calculating weight increase:

$$\Delta W_{ji,m(n+1)} = \eta.\delta_{j,m}.O_{i,m-1} + \alpha.\Delta W_{ji.m(n)} \quad (11)$$

In this equation $\Delta W_{ji,m(n+1)}$ is the amount of change in coefficient of weight between j and i neuron on n repeat and $\Delta W_{ji,m(n+1)}$ is the amount of change in coefficient of weight between j and i neuron on n+1 repeat. η is training rate and α is momentum ($0 \le \alpha,\eta \le 1$).
4-3. Updating weights.

$$\Delta W_{ji,m(n+1)} = \Delta W_{ji.m(n)} + \Delta W_{ji.m(n+1)} \quad (12)$$

4-4: Return to second step and repetition of the processes (Ghodsian et al., 2003).

Bar River watershed is a sub-catchment of Kal-Shoor Drainage Basin (one of basins which has arid climate), located in Khorasan Razavi province, having area of 125.12 km^2, mean altitude of 2215.9 m from sea level, mean annual rainfall of 365 mm and mean temperature of 5.3ºC. Location of Bar Watershed and its hydrometric station which is called Ariyeh is shown in figure 4.

After controlling the accuracy of data and elimination of some incorrect data, 113 cases of water discharge-sediment discharge data were used (table 1). In neural network method, first a number of data that are representative of all possible conditions, are selected for network training and the rest are used to test trained network operation. The important point in selecting the test data is that they contain a wide range of all kind of data. Therefore in selecting the test data we should be careful that they do not contain the maximum and minimum values and also for creating the maximum of similarities between the test and training data sets, the means and standard deviations of two series(test and trainning data) should be close together (Ghodsian et al., 2003). With regard to these points, about 80% of data were finally used for training and 20% of the rest for testing MLP network.

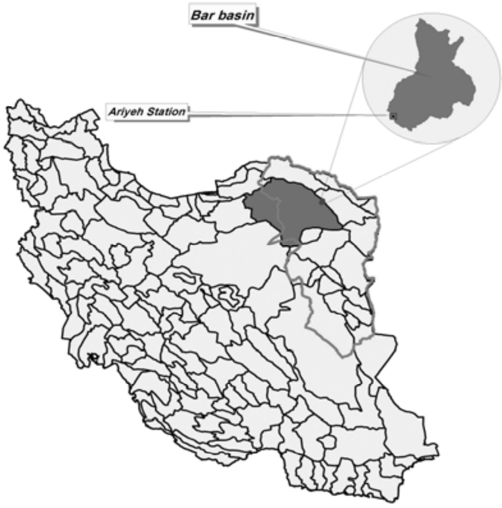

Fig. 4. Situation of Bar Watershed in Iran

Table 1. Range of usable data

Parameter	Water discharge (CMS)	Sediment discharge (Ton/day)
Maximum	673	9980
Minimum	0.126	0.080
Mean	117.514	206.529
Standard deviation	117.161	1003.775

The other important point is that we must normalize the data before entering them into the network. Principally, entering the raw data into the network reduces speed and precision of the network (Avarideh et al., 2002). To avoid such condition and for equalizing the value of data for network, normalizing was done according to following equation:

$$X_n = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (13)$$

In this equation, X_i is indicator of observation data, X_{max} and X_{min} are maximum and minimum amounts of data, respectively and X_n is normalized data. It is necessary to mention that in order to normalize water and sediment discharges, logarithm of data is used in equation 13.

In this research Neuralwork software (version 3.0) was used.

3. Results

3.1 .Final Model

After entering input patterns into network and defining a neuron for input and a neuron for output layers and performing repeated trial and error, optimum architecture (topology) of MLP network was stated as table2.

Table 2. Details of final network structure

3	Number of neurons for first hidden layer
1	Number of neurons for second hidden layer
1	Number of neurons for third hidden layer
Hyperbolic tangent	Activation function for first hidden layer
Hyperbolic tangent	Activation function for second hidden layer
Linear	Activation function for third hidden layer
Linear	Activation function for output layer
0.5	Learning rate
0.7	Momentum coefficient
75000	Number of epochs

With regard to performed trials and errors, it was clear that performing hyperbolic tangent function to Ariyeh station data can produce less RMS and better fitting of predicted data with observed (sampled) data (Figures 5 to 11). In MLP network if linear function is used in output layer and third hidden layer instead of using hyperbolic tangent activation in all layers, network is learned faster and moves toward the maximum data.

It must be considered that too much repetition causes reduction of network generalization ability (Murray, 1993). The other point is that learning rate is variable during time in such a way that it is 0.5 in the beginning of training and has a descending trend during training, and this is because the necessary condition for network convergence is satisfied.

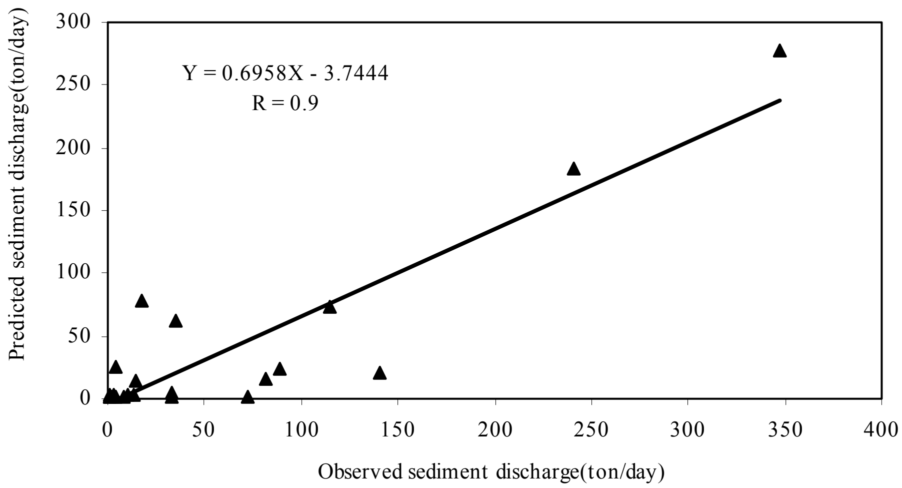

Fig. 5. MLP network test with TANH threshold function

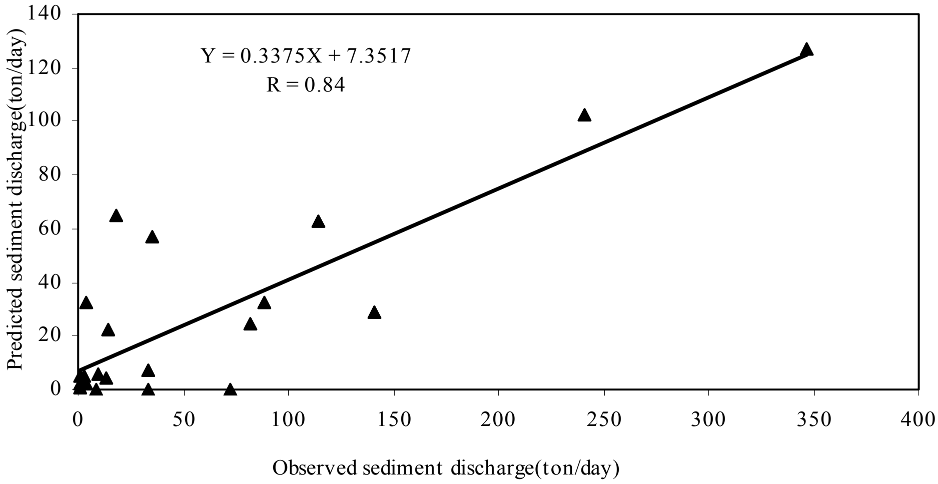

Fig. 6. MLP network test with sigmoid threshold function

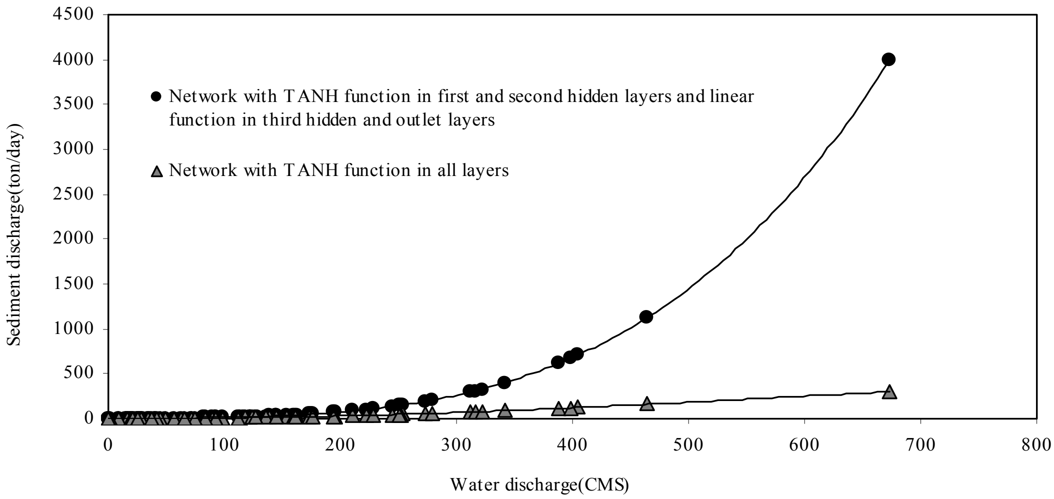

Fig. 7. Created mappings by MLP with applying different activation functions for layers.

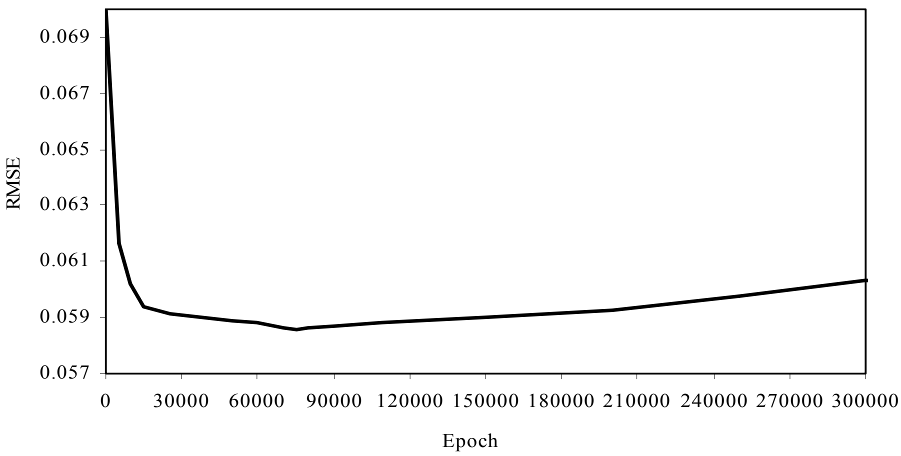

Fig. 8. RMSE graph for MLP network with TANH threshold function for the first and second hidden layers and linear for the third and output layers

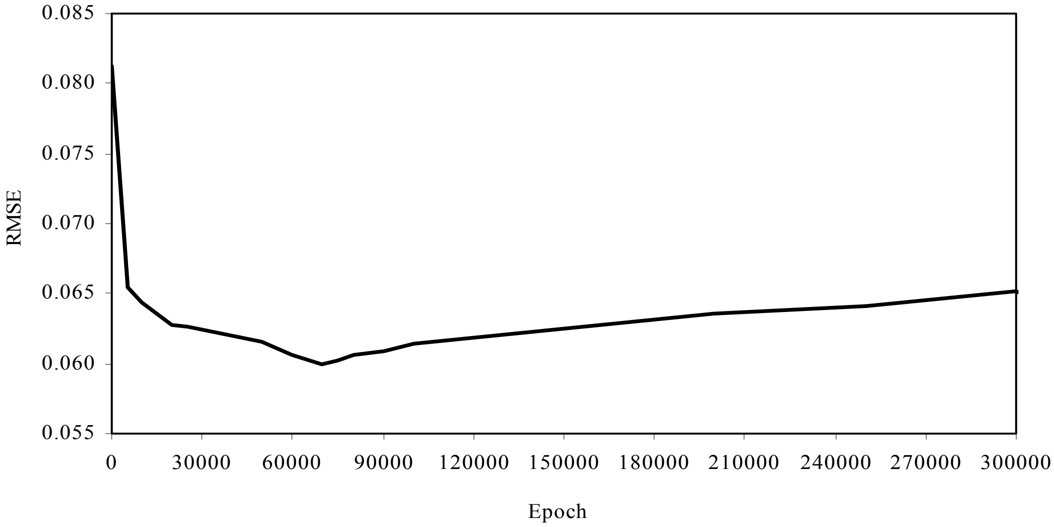

Fig. 9. RMSE graph for MLP network with TANH threshold function for all layers

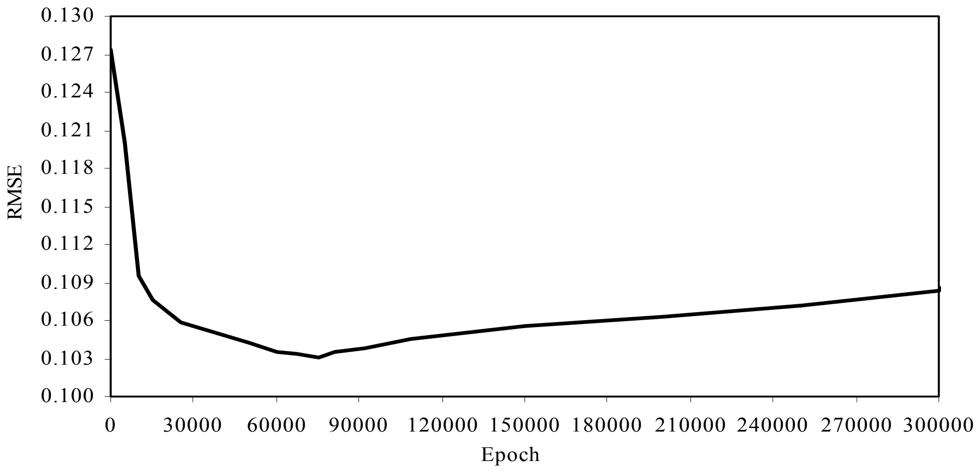

Fig. 10. RMS error graph for MLP network with sigmoid threshold threshold function for the first and second hidden layers and linear for the third and output layers

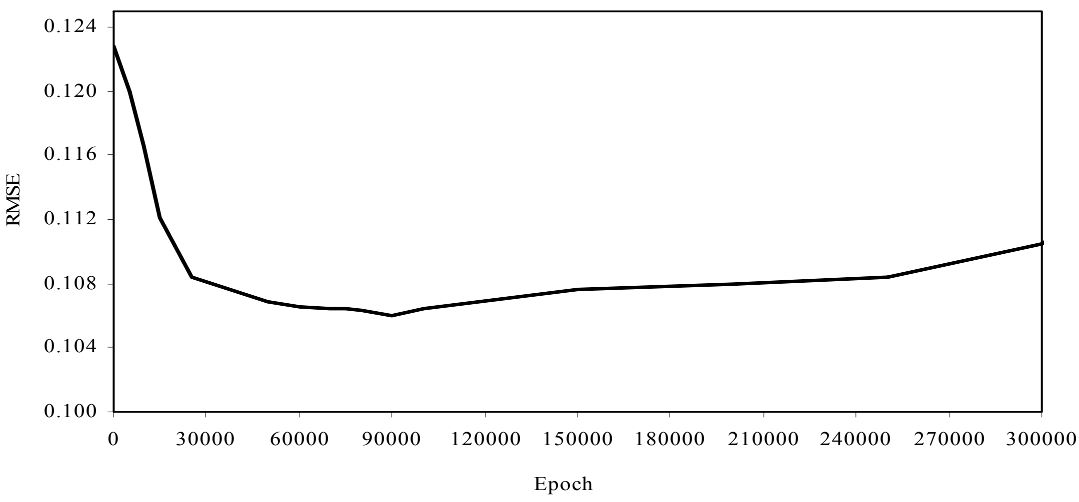

Figure 11. RMS error graph for MLP network with sigmoid function for all layers.

Indeed, having variable gain rate during training causes the network to avoid the local minimums at the beginning of training. As it is shown in figure 12, the optimum number of neurons for hidden layers was distinguished to be 5 which are placed as 3, 1, 1 in order in the first, second and third layers.

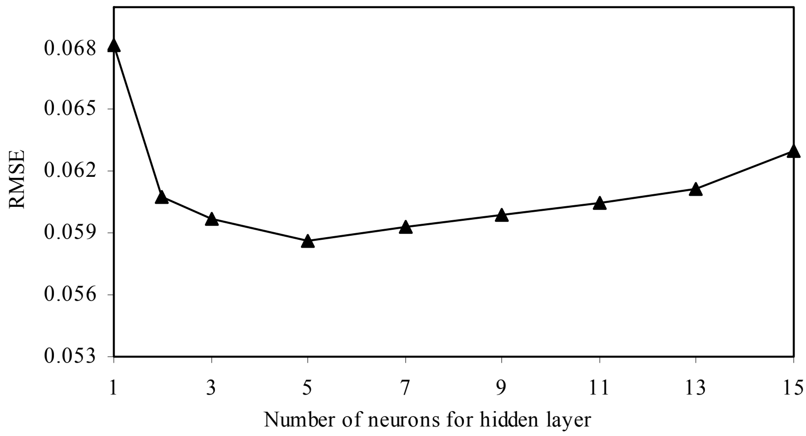

Fig. 12. RMSE graph for the different number of hidden layer neurons

Created mapping by MLP network on the basis of training data, with hyperbolic tangent threshold function for all layers and for the first and second hidden layers and linear function for the third hidden and output layers are shown in figure 7. As it is clear from the graph, mapping in which linear function is used for the third hidden and output layers shows the tendency of the graph toward maximum data in a better way

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Finally, MLP network in accordance with power equation curve of $Q_s=0.00047Q_w^{2.418}$ which was fitted on training data is shown in figure 13 and MLP network with other 22 data which are tested on the basis of mapping curve equation is shown in figure 14. In figure 14, predicted sediment yield is shown against observed sediment yield. The conclusion is optimum operation of MLP network.

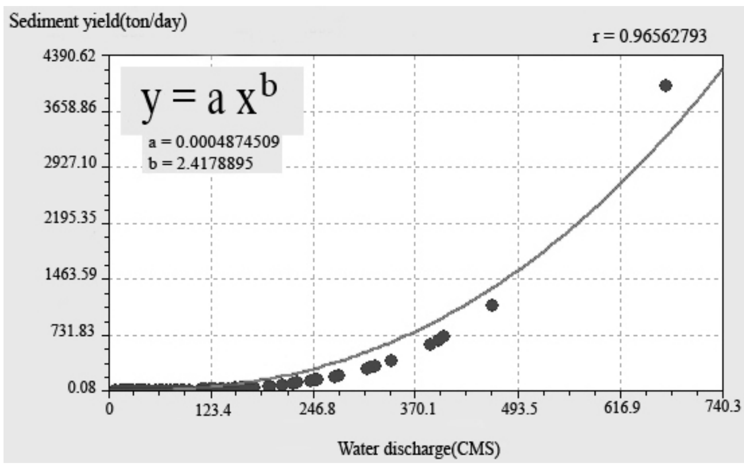

Fig. 13. Power curve fitting on mapping from MLP network

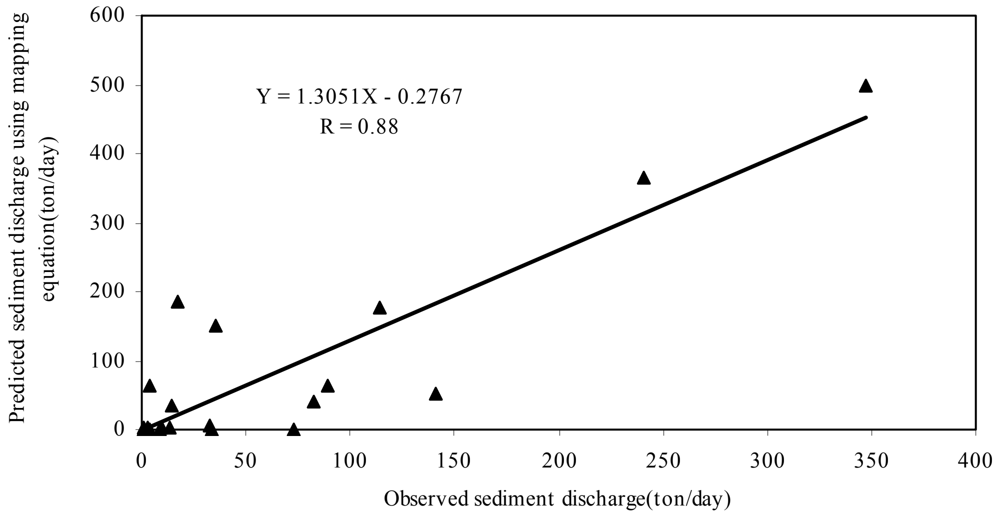

Fig. 14. MLP network test on the basis of mapping curve equation

The ability of this kind of network is often in creating non-linear mapping between two input and output multi-dimensional spaces with great sizes. Therefore the ability of this network is clearer when the other effective parameters such as rainfall depth and intensity, gradation of materials and even mean daily temperature are added to the network inputs.

4. Discussion and conclusions

One of the most important abilities of neural network is learning ability through presenting examples without requiring equations related to the phenomenon (Montazer et al., 2003). MLP network is creator of an ascending mapping, which can estimate high sediment discharges with hyperbolic tangent activation function on the first and second hidden layers and linear function on the third hidden and output layers and can be used to determine sediment rating curve. Comparison of estimations obtained from common statistical method with the power form of $Q_s=0.000335Q_w^{2.61}$ with the estimation obtained from MLP network, showed that the correlation coefficient between predicted and observed sediment yields is more in the second method (r=0.88) than that the first method (r=0.81), although this difference was not very significant but it indicated the higher precision of neural network.

The reason for this little difference could be due to little sampling especially during the high flood events, in the case of using a longer, more accurate and continuous statistical data, better results could be obtained using MLP neural network. But unfortunately water discharge and sediment discharge data is incomplete in the most of Khorasan province hydrometric stations and incorrect in some cases and this subject can be considered as a limiting factor in using neural network.

Another limiting factor is that neural network is not able to extrapolate and if it extrapolates, the error is high. Consequently for predicting the sediment yield of water discharges that are not in the range of training data, we will have difficulties. In these cases, it is better to use mapping equation resulting from neural network. Due to not recording water temperature in Ariyeh Hydrometric Station, the effect of this parameter on MLP network operation could not be investigated, with due attention to standing the Bar basin in the semi-arid area if the temperature and precipitation data are available, we can investigate the effect of daily or monthly mean temperature and also the amount of daily precipitation on the neural network operation.

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