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Investigation and Evaluation of Artificial Neural Networks in Babolroud River Suspended Load Estimation

Eassa Kia[1]*, Ali Reza Emadi[2], Ramin Fazlola[3]

[1]*M.Sc. student, Department of Water Engineering, Sari Agricultural Sciences and Natural Resources University, Sari, Iran*
[2]*Assistant Professor, Department of Water Engineering, Sari Agricultural Sciences and Natural Resources University, Sari, Iran*
[3]*Assistant Professor, Department of Water Engineering, Sari Agricultural Sciences and Natural Resources University, Sari, Iran*

*Corresponding author's Email address: eassa_kia@yahoo.com

ORIGINAL ARTICLE

ABSTRACT: Estimation of sediment load is a priority of the river management, dam's reservoirs and generally water projects. Because of nonlinear structure of sediment phenomena, the classical and common methods like sediment rating curve is not able to estimate sediment rate correctly. In recent years, artificial intelligence methods such as ANNs are recommended for solving the nonlinear problems and to achieve closer result to the actual data. In the present study, various combinations of flow discharge and sediment rate in present and past days were used as input parameters, while the suspended sediment load was used as output of the model. Then, by use of MATLAB software and different Neural Network such as MLP, RBF and GRNN, optimum architecture of networks is obtained based on four statistical indices viz. mean square error, mean bias error, modeling efficiency and determination coefficient for Ghoran Talar station in Babolroud River to compare with sediment rating curve. The results showed that MLP with combination of current discharge for estimate of current sediment has a better precision than other two neural networks. Also, the use of artificial neural network has a better performance than sediment rating curve method and recommended for river suspended load estimation.

Keywords: Suspended Load, Perceptron, Neural Network, Rating Curve

INTRODUCTION

Estimation of sediment load is important to a wide range of water resources projects, such as the design of dams and reservoirs, sediment and pollution transport in rivers and lakes, channel design and maintenance. The need for accurate modeling of suspended sediment has rapidly grown during the past decades in water resources and environmental engineering (Rajaee et al., 2009).

One of the approach to estimate the sediment load is the use of mathematical models and solution the hydrodynamic equations. These models require various hydraulic data and often data don't exist completely. So, the researchers have been suggested sediment rating curve method based on relating stream flow to sediment discharge and fitting the curve on the data (Cobaner et al., 2009; Coulibaly and Baldwin, 2005; Kisi et al., 2006; Rajaee et al., 2009). But, because of complexity and nonlinear relation between flow and sediment discharge, sediment rating curves are not able to model it sufficiently. So, the researchers tried to find other techniques to make more accurate modeling. In this case, Artificial Neural Network System (ANNs) have been used in a widely for modeling the nonlinear relationship in environment and hydrology engineering. This approach can make a logical connection between input and output by observed data.

Recent experiments have reported that ANN technique may offer a promising alternative for suspended sediment estimation (Jain, 2001; Tayfur, 2002; Cigizoglu, 2004; Kisi, 2004; Cigizoglu and Kisi, 2005; Cobaner et al., 2009; Melesse et al., 2011). Jain (2001) used a single ANN approach to establish the sediment-discharge relationship and found that the ANN model could perform better than the sediment rating curve. Tayfur (2002) developed an ANN model for sheet sediment transport and indicated that the ANN could perform as well as, in some cases better than, physically-based models. Cigizoglu (2004) investigated the accuracy of a single ANN in the estimation and forecasting of daily suspended sediment data. 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. Cigizoglu and Kisi (2005) developed methods to improve ANN performance in suspended sediment estimation. Cobaner et al. (2009) modeled suspended sediment concentration using hydro-meteorological data. 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.

According to the conducted studies and complexity of sediment phenomenon, further studies and more detailed

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investigation on new techniques such as ANN is absolutely necessary in suspended sediment load estimation. Therefore, the aim of this research is development of the models by use of ANN and compare their performance with sediment rating curve (SRC) based on the time series of the stream flow and sediment rate data to investigate capability and accuracy of conventional and artificial intelligence method in suspended sediment prediction. In this case, the suspended loads are estimated by three model of ANN (MLP, RBF and GRNN) technique in Ghoran Talar station located in Babolroud River and compared to SRC method.

MATERIALS AND METHODS

The Study Area

Babolroud river with a catchment basin more than 450 square kilometer originates from the northern mountains of Iran and underway in mountainous section. According to the daily sediment and flow data records (1977-2000) available in Ghoran Talar watershed, this basin selected for research (Figure 1). Ghoran Talar station located in Mazandaran province in the north of Iran in longitude of 52° 46′ E and latitude of 36° 19′ N. All data are collected from Mazandaran regional company.

Before any attempt to analyze the data; Run test, Markous method and correlation factor between adjacent stations are used in order to ensure the quality, uniformity and adequacy of the statistical series, respectively. Then, data were divided into two parts, 80% for training and 20% for the test. If a large disparity range occurs in the training and testing data, prediction by the artificial intelligence method will be poor.

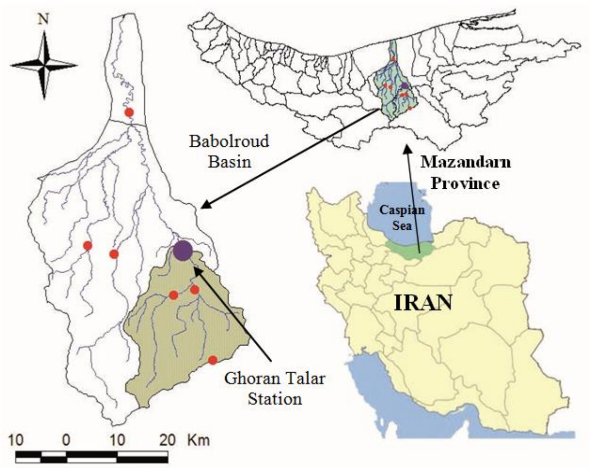

Figure 1. The location of Ghoran Talar station in IRAN

Therefore, to select the data, the method of trial and error have been used, so that the statistical indices viz. mean and standard deviation values are the same and extreme value are located in the training classes. The statistical parameters of stream flow and sediment rate data of Ghoran Talar station are shown in table 1. In this table, S_x, C_v and C_{sx} denote the standard deviation, variation and skewness coefficients, respectively. It can be seen from the skewness coefficient result that the stream flows and sediment data show scattered distribution. The ratio between standard deviation and mean, C_v, is also high for the station. All these statistics indicate the complexity of the discharge-sediment phenomenon.

Table 1. Statistical parameters of data set for the station

Statistical parameters	Training set		Testing set	
	Q_w (m^3/s)	Q_s (ton/day)	Q_w (m^3/s)	Q_s (ton/day)
Mean	7.00	207.91	5.34	157.31
Max	49.25	8305.29	16.00	2896.58
Min	0.10	0.27	0.35	5.32
S_x	7.09	681.29	3.54	344.91
C_v	1.01	3.28	0.66	2.19
C_{sx}	2.95	7.68	0.96	7.06

Finally, to make the models and estimate the sediment rate, the following combinations were used as the input of neural networks.

1. Q_t
2. Q_{t-1}
3. Q_{t-2}
4. Q_{t-3}
5. Q_t ,Q_{t-1}
6. Q_t , Q_{t-1} , Q_{t-2}
7. Q_t , Q_{t-1} , Q_{t-2} , Q_{t-3}
8. Q_t , $Q_{s(t-1)}$
9. Q_t , Q_{t-1} , $Q_{s(t-1)}$
10. Q_t , Q_{t-1} , Q_{t-2} , $Q_{s(t-1)}$, $Q_{s(t-2)}$
11. Q_t , Q_{t-1} , Q_{t-2} , Q_{t-3} , $Q_{s(t-1)}$, $Q_{s(t-2)}$, $Q_{s(t-3)}$

Where, Q_t and $Q_{s(t)}$ are stream flow and suspended sediment rate in time t. the output contains only current day of sediment rate.

Sediment rating curve (SRC)

The sediment rating curve depicts an empirical relationship between suspended sediment load and stream flow (Cigizoglu and Kisi, 2005; El-Bakyr, 2003). This relation is usually defined as a power function of the form of: $Q_S = a\,Q_W{}^b$ (1)

In which, a and b are coefficient of the equation and are obtained from least square error method or draw a line of best fit. The best fit line equation is then used together with stream flow data to estimate suspended sediment transport rates or to analyze other sediment related process.

Artificial Neural Network (ANN)

Artificial neural network (ANN) is a simplified model of a biological nervous system. An ANN consists of a number of data processing elements called neurons or nodes that are grouped in layers. The input layer neurons receive input data or information and transmit the values to the next layer of processing elements across connections. This process is continued until the output layer is reached. This type of network in which data flows in one direction (forward) is known as a feed-forward network (Tayfur, 2002). In practice, the ANN architecture consists of input layer, intermediate layers (hidden layer) and output layer. The hidden layers may be one or more depending on the data type and the model error statistics (Specht, 1991).

The main differences between the various types of ANNs are arrangement of network architecture and the many ways to determine the weights (w) and functions for inputs and training architecture (Cigizoglu, 2004). Three of the most widely used neural network in water engineering named MLP, RBF and GRNN are employed throughout the study.

Multi-layer perceptron network (MLP)

Among the applied neural networks, the feed forward neural network (FFNN) with back-propagation (BP) algorithm are the most popular used method in solving various engineering problems (Mesut, 2008). Back propagation was developed and popularized by Rumelhart et al. and it is widely implemented of all neural network algorithms (Schalkoff, 1997). It is based on a multi-layered feed forward topology with supervised learning.

The Multi-layer perception (MLP) is a feed forward network and has been designed to function well in capturing non-linear phenomena (Poggio and Girosi, 1990). Detailed information about MLP is found in literature (Rumelhart and McClelland, 1986; Taurino et al., 2003). A MLP consist of one hidden layer with Tansig transfer function and a Purelin transfer function in output layer (Figure 2) is capable of approximating any finite nonlinear function with very high accuracy (Kim et al., 2004).

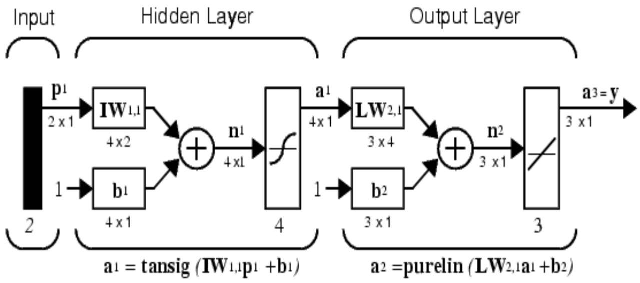

Figure 2. A two-layer MLP neural network structure

The Tansig transfer function (hyperbolic Tangent sigmoid) is given as Sarangi and Bhattacharya (2005):

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \qquad (2)$$

In MLP networks, using the Levenberge Marquardt (LM) technique is more powerful than the conventional gradient descent techniques (Hagan M.T, Menhaj, 1994; Cobaner, 2009). It was also found that in many cases the Marquardt algorithm converged when other back-propagation techniques failed to converge (Jain, 2001).

In the present study, the MLP network was trained using LM technique and the number of hidden layer neurons was found by simple trial-error method. The MLP network training stopped after 100 epochs since the variation of error was too small after this epoch.

Radial basis function network (RBF)

RBF networks were introduced into the neural network literature by Broomhead and Lowe (1988). The RBF network model is motivated by the locally tuned response observed in biological neurons. Neurons with a locally tuned response characteristic can be found in several parts of the nervous system, for example, cells in the visual cortex sensitive to bars oriented in a certain direction or other visual features within a small region of the visual field (Poggio and Girosi, 1990). These locally tuned neurons show response characteristics bounded to a small range of the input space. The theoretical basis of the RBF approach lies in the field of interpolation of multivariate functions. The RBF structure is shown in Figure 3. The interpretation of this approach as an artificial neural network consists of three layers: a layer of input neurons feeding the feature vectors into the network; a hidden layer of RBF neurons, calculating the outcome of the basis functions; and a layer of output neurons, calculating a linear combination of the basis functions (Taurino et al., 2003).

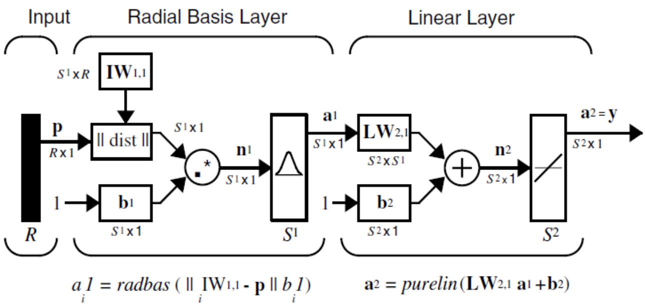

Figure3. the structure of RBF neural network

General Regression Neural Network (GRNN)

A GRNN is a variation of the radial basis neural networks, which is based on kernel regression networks (Kim et al., 2004; Celikoglu, H.B, Cigizoglu, 2007). In the literature, the fundamentals of the GRNN can be obtained (Specht, 1991; Tsoukalas and Uhrig, 1997). A GRNN does not require an iterative training procedure as back propagation networks. It approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data (Kim et al., 2004). As it can be seen from Figure 4, the Generalized Regression Network consists of three layers of nodes with entirely different roles: The input layer, the output layer and the hidden layer, where a nonlinear transformation is applied on the data from the input space to the hidden space.

The learning of GRNN is faster than MLP network. It doesn't produce the negative values. The most popular choice for the approximation function is a multivariate Gaussian function with an appropriate mean and auto-covariance matrix. The value of spread factor parameter in the function is often determined experimentally (Kim et al., 2003). If the spread becomes larger, the approximation function will be smoother. If spread is too large, a lot of neurons will be required to fit a fast changing function. Too small value of spread means many neurons will be needed to fit a smooth function, and the network may not generalize well.

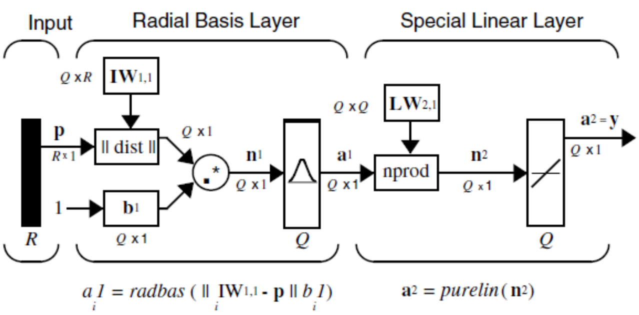

Figure4. the structure of GRNN neural network

Finally, mean square error (MSE), mean bias error (MBE), modeling efficiency (EF) and determination coefficient (R^2) statistics are applied as evaluation criteria, so as follows (Masters, 1993):

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$$MSE = \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{N} \quad (3)$$

$$R^2 = \frac{\left[\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O})\right]^2}{\sum_{i=1}^{n}(P_i - \bar{P})^2 \cdot \sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (4)$$

$$MBE = \frac{\sum_{i=1}^{n}(P_i - O_i)}{N} \quad (5)$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (6)$$

Where;

N: the number of data

$\bar{P}$: mean of predicted value by model

$\bar{O}$: mean of observed value

The estimation of total sediment load in test period obtained from the estimated suspended sediment values is also considered for comparison due to its importance.

RESULTS AND DISCUSSION

From 413 daily stream flow and sediment time series data belong to Ghoran Talar station, 338 daily data (80% of the whole data) are used for training and the remaining 75 daily data (20% of the whole data) for testing and determining the statistical indices to compare the proposed combinations. The data from October 1, 1977 to September 30, 1994 (17 years) and the data from October 1, 1994 to September 30, 2000 (6 years) are training and testing periods, respectively.

In order to use the ANN application, first, stream flow and sediment discharge are pre-processed by scaling them between 0 and 1 to equalize the importance of variables and to interpretability of the network weights (Hornik, 1989; Müller et al., 1995). The data can be scaled in any interval by using the following equations:

$$x'_i = \frac{x_i(B_u - B_L) + x_{max}B_L - x_{min}B_u}{x_{max} - x_{min}} \quad (7)$$

Where, (x_1, x_2, … , x_n) are mapped in the desired range [B_L,B_u]. x_{max} and x_{min} denote the maximum and minimum values of the overall data (Specht, 1991).

Application of MLP model

For training of Multi-Layer Perceptron (MLP) network, a program code, including neural network toolbox was written in MATLAB language. A three layer neural network with back-propagation algorithm (Caudill and Butler, 1992) which contains one input layer, one hidden layer and one output layer was applied to determine the number of neurons in hidden layer.

Since there is no specific algorithm to announce how many neurons are required in this layer for simulating functions? The number of neurons in the hidden layer was investigated by trial and error method with variation between 2 to 20 for each combination (1-11) to achieve the best network structure. In this case, first the training started with a fewer neuron and increased gradually. When the training stage was completed, the testing stage began using the optimum value found for the number of neurons. The Tansig and Purelin functions were utilized as transfer functions in hidden and output layers. The results of modeling by MLP with its statistical indices are shown in table 2.

According to table 2, the optimum number of neurons for all combinations obtained less than 8 and shows that, whatever number of layer and the number of its neurons are less, the network has better structure. From input combination 2 to 4, the determination coefficient (R^2) reduces respectively and indicated that sediment discharge on each day is more related to the stream flow of the same day. Moreover, whatever stream flow is belonged to the earlier days, correlation with the sediment of the same day is less, which seems reasonable.

Table 2. The optimum structure and testing performance of MLP model in suspended sediment estimation

Input no.	Optimum structure	MSE	MBE	EF	R^2
1	1-6-1	0.087	0.006	0.760	0.67
2	1-7-1	0.33	0.30	0.10	0.09
3	1-4-1	0.30	0.27	0.11	0.06
4	1-6-1	0.44	0.41	-0.22	0.00
5	2-5-1	0.49	0.54	-0.33	0.38
6	3-2-1	0.17	-0.04	0.54	0.72
7	4-8-1	0.09	-0.012	0.762	0.67
8	2-6-1	0.088	0.06	0.77	0.72
9	3-3-1	0.19	0.25	0.47	0.66
10	5-5-1	0.29	0.33	0.21	0.68
11	7-6-1	0.43	0.48	-0.19	0.22

In the models where stream flow on previous day added to the current stream flow (input combination 5 to 7), increases the model performance. Input combinations 8-11 are obtained adding the previous suspended sediment values into the input combination 1, 5, 6 and 7. In these combinations, MSE and MBE increase while EF and R^2 decrease respectively.

In the models, where only stream flow is the input (input combination 1), the MLP model has the best accuracy according to MSE, MBE and EF statistics. But, the R^2 view point, it is not the best. Note that the R^2 term provides information for linear dependence between observation and corresponding estimates. So, it is not always expected that R^2 is in agreement with performance criteria such as MSE or EF.

Therefore, input combination 1 with a one hidden layer and 6 neurons in it has the optimum structure and is the best model of MLP method in the station.

Application of RBF and GRNN models

A program code was written in MATLAB language for the RBF and GRNN models simulation. In the training of the RBF and GRNN, spread factor is the only parameter which obtained by trial and error method and the optimum number of neuron is not required to determine unlike the MLP model. In this case, different coefficient values were tried using this code and the appropriate one were determined for each input combination. Then, these two models were tested and the results were compared by statistical indices. The final structure in the training period and the results of statistical indices in the test period are given in table 3.

According to the table 3, the value of spread factor is obtained 0.1-32 for the RBF and 0.4-3.8 for the GRNN model. Moreover, the results of RBF and GRNN are same as MLP model. So, the first combination (only current stream flow as an input) has better results compared to other combinations from the statistical criteria viewpoint and is introduced as an optimum RBF and GRNN models in the station.

Table 3. The results of training and testing of the RBF and GRNN models - Ghoran Talar station

Input no.	Spread factor		Training phase				Test phase							
			RBF		GRNN		RBF				GRNN			
	RBF	GRNN	MSE	R^2	MSE	R^2	MSE	MBE	EF	R^2	MSE	MBE	EF	R^2
1	21	1.5	0.29	0.68	0.27	0.76	0.12	-0.06	0.66	0.58	0.09	-0.03	0.75	0.70
2	20	3.8	0.72	0.49	0.78	0.45	0.37	0.32	-0.01	0.05	0.34	0.31	0.06	0.07
3	20	2.8	0.73	0.47	0.80	0.43	0.45	0.30	-0.30	0.01	0.40	0.36	-0.17	0.00
4	30	0.4	0.88	0.32	0.73	0.37	0.39	0.32	-0.08	0.00	0.37	0.24	-0.02	0.00
5	27	2.2	0.33	0.64	0.27	0.78	0.22	-0.09	0.30	0.46	0.10	0.00	0.73	0.63
6	28	2.5	0.31	0.65	0.26	0.79	0.56	0.01	-1.00	0.19	0.13	0.01	0.64	0.51
7	32	2.2	0.24	0.74	0.18	0.86	0.87	0.56	-1.27	0.20	0.13	-0.02	0.65	0.52
8	0.4	3.0	0.026	0.61	0.22	0.83	0.29	0.21	0.20	0.06	0.24	0.03	0.33	0.15
9	0.7	2.8	0.39	0.58	0.18	0.85	0.24	0.02	0.34	0.13	0.22	0.01	0.39	0.19
10	0.6	3.5	0.65	0.54	0.12	0.83	0.37	0.42	0.16	0.02	0.58	0.02	-0.57	0.04
11	0.9	3.5	0.84	0.47	0.15	0.79	0.52	0.57	-0.27	0.00	0.87	-0.12	-1.30	0.01

Sediment Rating Curve method (SRC)

Finally, the SRC technique was applied to the training data set. The following formula was obtained to offer the best statistical measures for fit of training data set:

$$Q_S = 11.74 Q_W^{1.30} \tag{8}$$

In which, Q_s is sediment discharge and Q_w is stream flow. In order to compare the results obtained from the use of SRC, MLP, RBF and GRNN approaches, statistical indices i.e. MSE, MBE, EF and R^2 for the four methods are shown in table 4.

Table 4. Application results of SRC and ANN methods in suspended sediment estimation

method	optimum combination	MSE	MBE	EF	R^2
SRC	Q_t	0.16	-0.30	0.57	0.73
MLP	Q_t	0.08	0.01	0.76	0.67
RBF	Q_t	0.12	-0.06	0.66	0.58
GRNN	Q_t	0.09	-0.03	0.75	0.70

As seen from the table 4, MLP model has the minimum MSE and MBE and the maximum EF between four models.

Also, from R^2 viewpoint, it has a good result. So, the accuracy of the MLP is slightly higher than the GRNN and these two models are better than the values attained by the RBF and SRC models in suspended load estimation. Kisi (2004) and Alp et al. (2007) are obtained similar results in their study area.

The logarithm scaled scatter plots of the best model (combination 1) are plotted by SRC, MLP, GRNN and RBF models for the test period in Figure 5.

As can be seen from Figure 5, the estimates of MLP model are closer to the exact fit line than those of the other models. It seems that MLP has less scattered data than the others. The underestimations of the SRC model are obviously seen, too.

Moreover, the observed and estimated suspended sediment value for four methods in test period is shown in Figure 6. It is seen that MLP technique estimates more closely follow the observed values. GRNN and RBF results are close to the observed data but, underestimate it in some points and their performance are better than the SRC.

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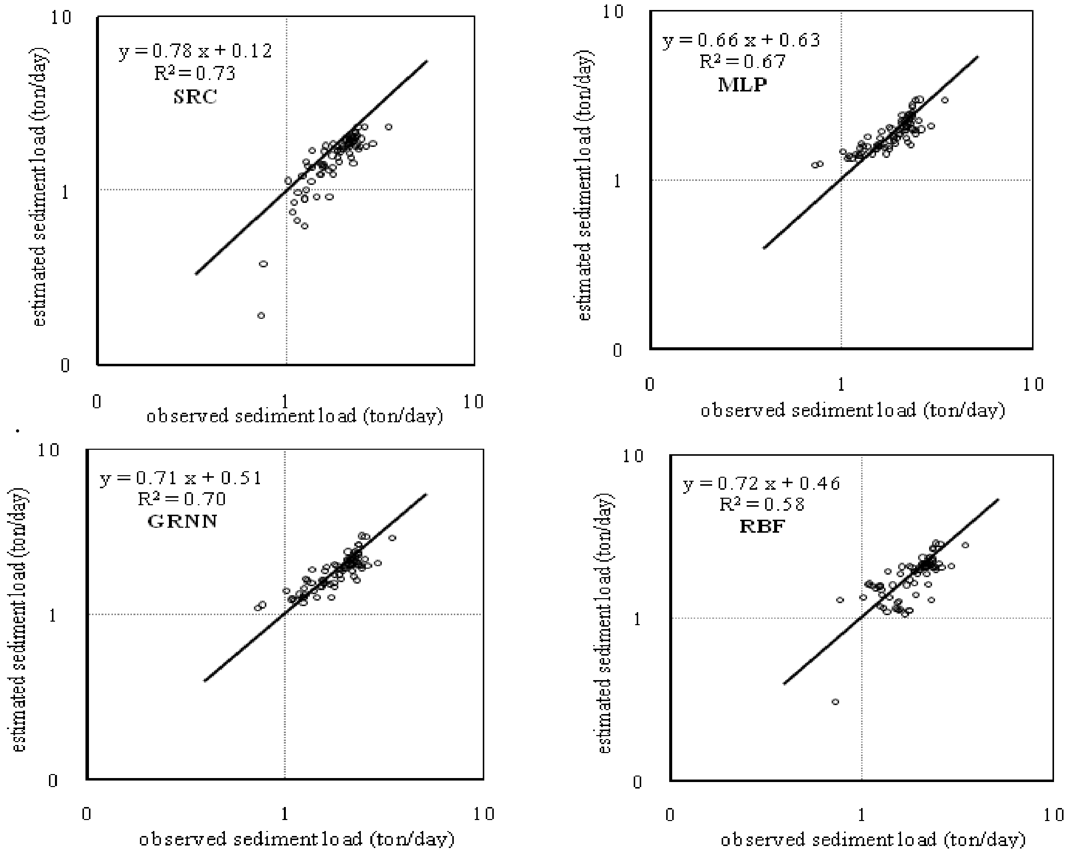

Figure 5. Scatter plots of observed and predicted suspended sediment by SRC, MLP, GRNN and RBF models for the test period

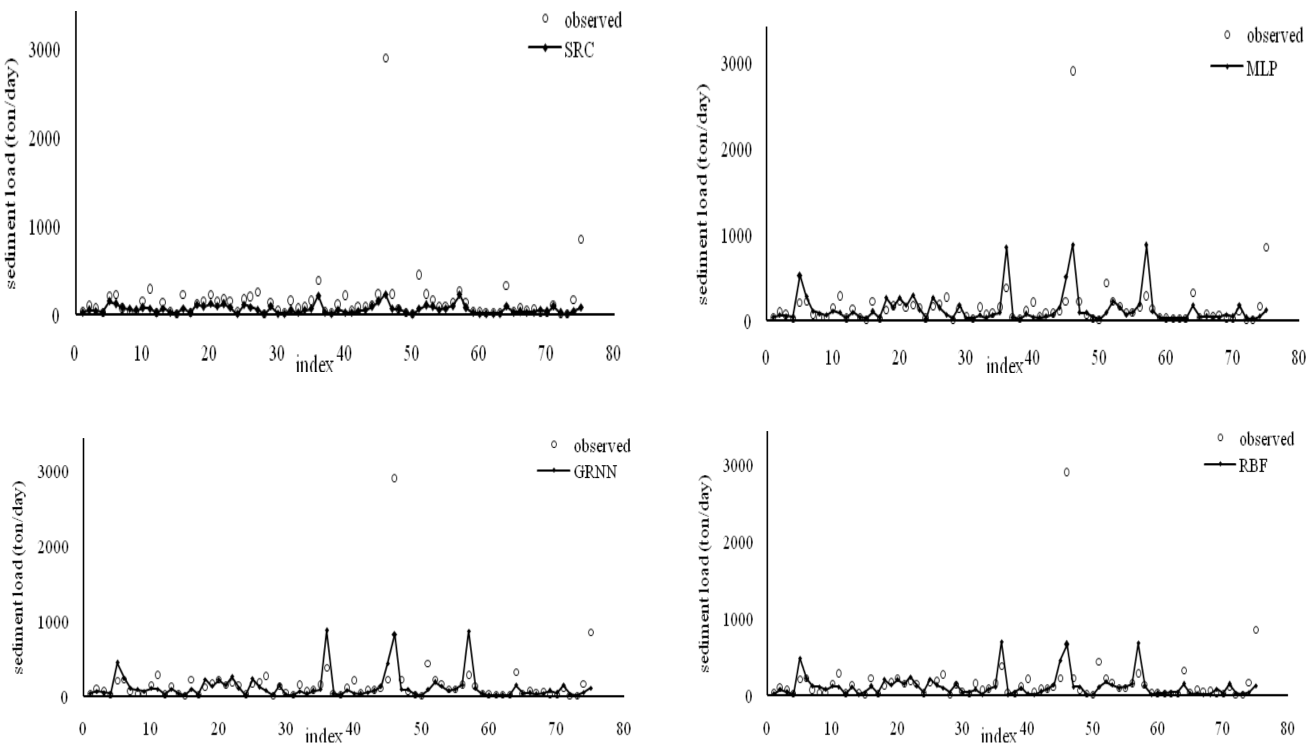

Figure 6. Comparison of observed and estimated data by SRC, MLP, GRNN and RBF methods in test period

Table 5. Estimated total suspended sediment load in test period

	Observed	SRC	MLP	GRNN	RBF
Estimated (ton)	11798.1	4398.2	9793.2	9060.8	8664.3
Relative error (%)		-62.7	-17.0	-23.2	-26.6

The estimation of cumulative suspended sediment load which is essential component for comparison due to its importance in reservoir management was also considered as another comparison criterion. The total estimated sediment values in test period are given in table 5.

From the table 5, the observed total sediment load in test period was 11798.1 ton in the Ghoran Talar station. The SRC, MLP, GRNN and RBF models underestimated it 62.7%, 17.0%, 23.2% and 26.6%, respectively. So, the MLP model presented a better performance in comparison with the other models. The GRNN and RBF also seem to be much better than the SRC model in estimating suspended sediment load. The results are also tested by using one way analysis of variance (ANOVA) for verifying the significance differences between the model estimates and observed values. The test is set at a 95% significant level. The statistics of the test is given in table 6.

Table 6. Analysis of variance for suspended sediment load estimation in test period

	SRC	MLP	GRNN	RBF
F-statistic	3.01	0.21	0.67	0.94

According to the test results, all F-value is higher than 0.05. However, the MLP seems to be more robust, but, there is no significance difference between the models. Therefore, according to the results of statistical indices, scatter plots and comparison of observed and estimated data, it is seen that MLP model can estimate the suspended sediment load better than GRNN, RBF and SRC models. Also, among the combinations used in this research, combination 1 i.e. current stream flow as input is the optimum model in the studied station.

CONCLUSIONS

In the present study, suspended sediment load was estimated by SRC, MLP, GRNN and RBF methods. In this case, several input combinations including daily stream flow of current and previous days and suspended sediment rate of previous days were used as input parameters to estimate current suspended sediment load. It was found that the MLP model, whose input is current stream flow, has the best accuracy. Also, the comparison results between four applied models reveal that the MLP model perform better than GRNN, RBF and SRC models in daily suspended sediment load estimation. Furthermore, The GRNN and RBF models provided better estimates than the conventional SRC method. The superiority of ANNs over conventional SRC method in the simulation of sediment load series is evident, because the ANNs are able to capture the nonlinear dynamics and generalize the structure of the whole data set. They are a flexible alternative and standard ANN software can be used to construct intricate multi-purpose nonlinear solutions. The method has no limitations in the form of fixed assumptions or formal constraints. The neural network has a distributed processing structure.

In order to improve the current research, other hydro-meteorological data such as precipitation can be tested as an input parameter in all models and analyzed the effect of them in models accuracy. Also, it is suggested that the results of this research is used in other stations to investigate more and more the potential of these new computing techniques.

REFERENCES

ASCE Task Committee. (2000). Artificial neural networks in hydrology, J Hydro Eng ASCE, 5(2): 124-37.

Broomhead D., Lowe D. (1988). Multivariable functional interpolation and adaptive networks, Complex Systems, 2: 321-355.

Campbell F.B., Bauder H.A. (1940). A rating curve method for determining silt-discharge of streams, Transactions of the American Geophysical Union, 21: 603-607.

Caudill M., Butler C. (1992). Understanding Neural Networks, Vol. 1: Basic Networks, the MIT Press, Cambridge, MA.

Celikoglu H.B., Cigizoglu H.K. (2007). Public transportation trip flow modeling with generalized regression neural networks, Adv Eng Software, 38: 71-9.

Cigizoglu H.K. (2004). Estimation and forecasting of daily suspended sediment data by multi-layer perceptrons, Advances in Water Resources, 27: 185-195.

Cigizoglu H.K., Kisi O. (2005). Flow prediction by two back propagation techniques using k-fold partitioning of neural network training data, Nordic Hydrology, 36 (1): 1-16.

Cobaner M., Unal B., Kisi O. (2009). Suspended sediment concentration estimation by an adaptive neuro-fuzzy neural network approaches using hysro-meteorological data, J Hydrology, 367: 52-61.

Coulibaly P., Baldwin C.K. (2005). Non-stationary hydrological time series furcating using nonlinear dynamic methods, J Hydrology, 307: 164-174.

Crawford C.G. (1991). Estimation of suspended sediment rating curves and mean suspended sediment loads, J Hydrology, 129: 331-348.

El-Bakyr M.Y. (2003). Feed forward neural networks modeling for K-P interactions, Chaos, Solitons and Fractals, 18 (5): 995-1000.

Goh A.T.C. (1995). Back-propagation neural networks for modeling complex systems, Artificial Intelligence in Engineering, 9: 143-151.

Hagan M.T., Menhaj M.B. (1994). Training feed forward techniques with the Marquardt algorithm, IEEE Transactions on Neural Networks, 5 (6), 989-993.

Hornik K., Stinchcombe M., White H. (1989). Multilayer feed forward networks are universal approximators, Neural Netw, 2(5): 359-66.

Jain S.K. (2001). Development of integrated sediment rating curves using ANNs, Journal of Hydraulic Engineering, 127 (1): 30-37.

Kim B., Kim S., Kim K. (2003). Modelling of Plasma Etching using a Generalized Regression Neural Network, Vacuum, 71: 497-503.

Kim B., Lee D.W., Parka K.Y., Choi S.R., Choi S. (2004). Prediction of plasma etching using a randomized generalized regression neural network, Vacuum, 76: 37-43.

Kisi O. (2004). Multi-layer perceptrons with Levenberge Marquardt training algorithm for suspended sediment concentration prediction and estimation, Hydrological Sciences Journal, 49 (6): 1025-1040.

Kisi O. (2010). River suspended sediment concentration modeling using a neural differential evolution approach, J Hydrology, 389: 227-235.

Kisi O., Karahan E., Sen Z. (2006). River suspended sediment modeling using a fuzzy logic approach, Hydro Process, 20 (20): 4351-62.

Lippman R. (1987). An introduction to computing with neural nets, IEEE ASSP Mag, 4: 4-22.

Masters T. (1993). Practical neural network recipes in C++, San Diego (CA): Academic Press.

Melesse A.M., Ahmand S., McClain M.E., Wang X., Lim Y.H. (2011). Suspended sediment load prediction of river systems: An artificial neural network approach, Agricultural Water Management, 98: 855-866.

Mesut C. (2008). Estimation of daily suspended sediment using support vector machines, J Hydrological Science, 53(3).

Müller B., Reinhardt J., Strickland M.T. (1995). Neural Networks: an Introduction, Springer-Verlag, New York, 52-62.

Poggio T., Girosi F. (1990). Regularization algorithms for learning that are equivalent to multilayer networks, Scienc, 2247: 978-982.

Rajaee T., Mirbagheri S.A., Zounemat-Kermani M., Nourani V. (2009). Daily suspended sediment concentration simulation using ANN and neuro-fuzzy models, Science of the Total Environment, 407: 4916-4927.

Rumelhart D.E., McClelland J.L. (1986). Parallel Distributed Processing: Explorations in the Microstructure of Cognition, vol. 1, the MIT Press, Cambridge, 318-362.

Sarangi A., Bhattacharya A.K. (2005). Comparison of artificial neural network and regression models for sediment loss prediction from Banha watershed in India, Agricultural Water Management, 78: 195-208.

Schalkoff R.J. (1997). Artificial Neural Networks, Mcgraw-Hill, New York, 146-188.

Specht D. F. (1991). A General Regression Neural Network. IEEE Trans, Neural Networks, 2 (6): 568-576.

Taurino A.M., Distante C., Siciliano P., Vasanelli L. (2003). Quantitative and qualitative analysis of VOCs mixtures by means of a microsensors array and different evaluation methods, Sensors and Actuators, 93: 117-125.

Tayfur G. (2002). Artificial neural networks for sheet sediment transport, J Hydrological Sciences, 47 (6): 879-892.

Tsoukalas L.H., Uhrig R.E. (1997). Fuzzy and Neural Approaches in Engineering, New York, John Wiley and Sons, Inc., 587p.

Yang C.T., Marsooli R., Aalami M.T. (2009). Evaluation of total load sediment transport formulas using ANN, J sediment Research, 24: 274-286.