O 80. USABILITY OF ARTIFICIAL NEURAL NETWORKS FOR SEDIMENT ESTIMATION

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ABSTRACT: Sediment estimation is very important as water resources projects with high costs cause the economic life of projects to decrease more quickly. In order to prevent the decrease in the economic life of the dam reservoirs and to reduce the sedimentation in the dam reservoirs, it is also necessary to determine the sediment carried by the river. Recently Artificial Neural Network (ANN) is widely used to solve the complex problems such as sediment. In this study, the flow (m^3/sec) and sediment (ton/day) data of the Söğütlühan Observation Station during the 1994-2011 periods in the Kızılırmak Basin are used for the sediment estimation. The results of ANN models and sediment rating curve method were compared. As a result of the comparison, it was seen that ANN models were more successful than sediment rating curve for sediment estimation.

Keywords: Artificial Neural Network, Kızılırmak Basin, Sediment, Sediment Rating Curve

1. INTRODUCTION

The utilization rate of hydraulic potential, which is one of the most important renewable energy sources, has become an indicator of the development and industrialization of countries. While the rate of utilization of hydraulic potential is 80% in developed countries, this rate is 25-30% in developing countries (EIE, 2000). Therefore, studies on the use of hydraulic potential are expected to increase in the future in developing countries. Dams are built on the rivers in our country for purposes such as agriculture, industry and drinking water, flood control and energy production. The sediment, such as soil, sand, silt, clay and gravel, which are carried by the streams that feed the lakes of dams, fill the dam reservoirs, reduce their storage capacity and consequently shorten the economic life of the dams (Kişi et al., 2003). In countries with semi-arid climate and a complex topography, such as Turkey, the correct calculation of sedimentation is quite important.

Determining the amount of sediment transported in rivers is of great importance for engineering as well as being a very difficult problem to examine. Due to the large number of geological, topographic and climatologically factors affecting sediment transport and their interrelationships being complex, it is difficult to calculate the amount of sediment carried by any river analytically.

The amount of suspended sediment load (SSL) in rivers can be determined by different methods such as direct measurements at sediment observation stations, sediment rating curve, regression, artificial intelligence methods and empirical approaches based on experimental studies (Ulke et al., 2010). Lafdani et al (2013) used ANN and SVM models as input for precipitation and flow data in daily SSL estimation in Doiraj River located in western Iran.

Although the sediment measurements performed at sediment monitoring stations are the most reliable way, they are disadvantageous in terms of time and cost. It is necessary to avoid possible errors by renewing the measured section in each measurement. Nowadays, with the development of computer technology, Artificial Neural Networks (ANNs) are widely used in prediction of sediment amount as in many fields. There are many studies on this subject in the literature (Nourani et al. 2016; Cigizoglu 2000; Yang, 1996; Melesse et al. 2011; Goyal 2014; Singh et al. 2013; Buyukyildiz and Kumcu, 2017). In this study, the usability of ANN models was studied to predict daily SSL of Kızılırmak River-Sögütlühan observation station in Kızılırmak Basin in Turkey.

2. MATERIAL and METHOD

2.1. Study Area

In this study, sediment estimation was made by using ANN models. Models were created in MATLAB program by using various combinations of inputs and flow and sediment data of Kızılırmak River-Söğütlühan sediment observation station in Kızılırmak Basin.

Some properties of the sediment observation station, whose data are used to estimate the sediment amount, are given in Table 1 and the location of the station in Kızılırmak Basin is given in Figure 1.

Table 1. Characteristics of Sediment Observation Station

Station No	Station Name	Altitude (m)	Location	Precipitation Area (km^2)	Observation Period
1535	Kızılırmak River-Söğütlühan	1243	36° 50' 34" E 39° 43' 02" N	6,472.4	1994-2011

Kızılırmak Basin is located between 41°44' - 38°25' N latitudes and 32°48' - 38°25' E longitudes. Kızılırmak Basin covers 10.49% of Turkey with 82,181 km^2 area. The annual total precipitation is 442.5 mm and the annual mean temperature is 10.5°C in the Kızılırmak Basin.

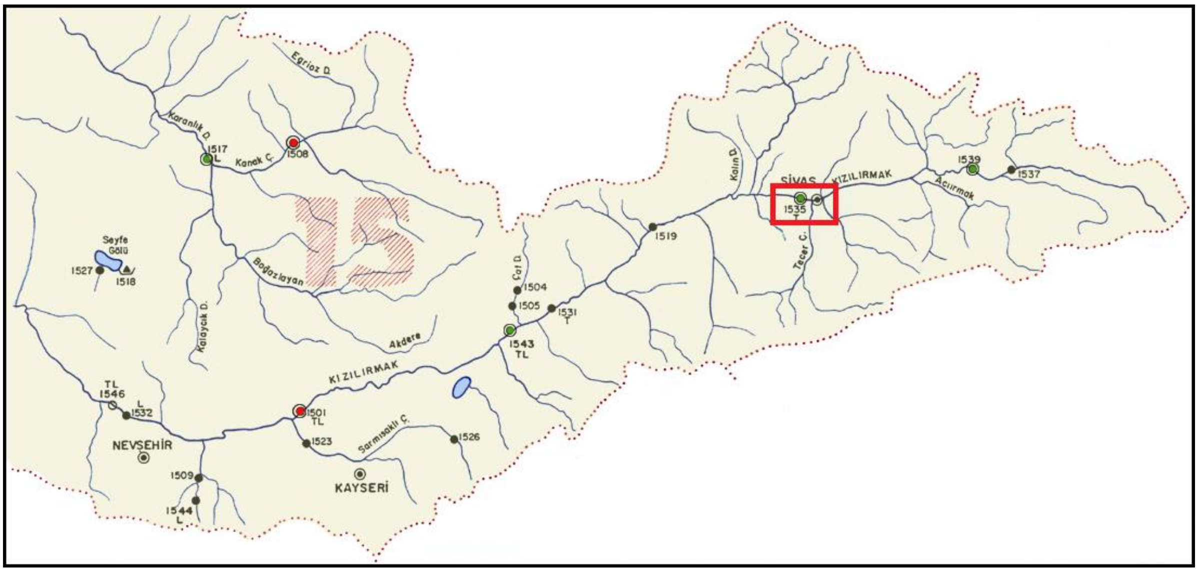

Figure 1. The Location of Kızılırmak River – Söğütlühan Observation Station (Station No:1535) in Kızılırmak Basin

2.2. Artificial Neural Network

ANNs, which are designed with inspiration from the human biological nervous system, can be considered as a black box that produces outputs against inputs. Learning in biological systems is made by the connections between nerve cells. ANNs, which are not limited to application areas, have a wide application area by successfully solving the problems encountered in many part of life. ANNs are characterized by the neuron model used, network connections of these neurons, the determination of the learning rule for adjusting the weight coefficients, and recall (Ülker ve Civalek, 2002). Many learning algorithms are used in ANNs. In this study, Multilayer Perceptron (MLP) and Radial Based Neural Networks (RBNN) were used.

In MLP working with supervised learning, the learning rule is the generalized version of the Delta Learning Rule based on the least squares method. In predicting performance of MLP, the number of hidden layers, the number of neurons in the hidden layer, learning rate, momentum coefficient, iteration number and activation function are effective.

RBNN, an ANN model based on human neurons in neurons, is a special case of multi-layer feed forward networks and was developed by Broomhead and Lowe (1988). It has two characteristics: having a single hidden layer and using radial based functions as activation function in hidden layer neurons (Akbilgiç, 2011). As in the classical ANN model, training takes place between input and output (Okkan and Dalkılıç, 2012). In RBNN models, fast solutions can be produced due to the small number of parameters required by the user.

2.3. Performance Criteria

The performance of the models was evaluated using the coefficient of determination (R^2), Nash Sutcliffe efficiency coefficient (E_{Nash}), mean absolute error (MAE) and root mean square error (RMSE). The equations are given below.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_{i_{observed}} - Y_{i_{estimated}}\right| \quad (1)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(Y_{i_{observed}} - Y_{i_{estimated}}\right)^2} \quad (2)$$

$$R^2 = \frac{\left[\sum_{i=1}^{N}\left(Y_{i_{observed}} - \overline{Y}_{observed}\right)\left(Y_{i_{estimated}} - \overline{Y}_{estimated}\right)\right]^2}{\sum_{i=1}^{N}\left(Y_{i_{observed}} - \overline{Y}_{observed}\right)^2 \sum_{i=1}^{N}\left(Y_{i_{estimated}} - \overline{Y}_{estimated}\right)^2} \quad (3)$$

$$E_{Nash} = 1 - \frac{\sum_{i=1}^{N}\left(Y_{i_{observed}} - Y_{i_{estimated}}\right)^2}{\sum_{i=1}^{N}\left(Y_{i_{observed}} - \overline{Y}_{observed}\right)^2} \quad (4)$$

3. RESEARCH FINDINGS

In this study, 256 sediment and flow data belonging to 1994-2011 period in Kızılırmak-Söğütlühan station were used. 70% (178) of the 256 data was used as training and 30% (78) was used as test data. In order to estimate the amount of SSL, data consisting of different delay time series of daily flow (Qt) and SSL (St) were used as input and SSL was used as output. The input combinations used are given in Table 2.

Table 2. Input combinations used in the study

Model Name	Inputs	Output
M1	St,Qt	
M2	St, St-1	
M3	St, St-1,Qt	
M4	St, St-1, St-2	
M5	St, St-1, St-2, Qt	S_t
M6	St, St-1, St-2, Qt, Qt-1	
M7	St, St-1, Qt-1	
M8	St, St-1, Qt, Qt-1	
M9	St, St-1, St-2, Qt-1, Qt-2	
M10	St, St-1, St-2, Qt, Qt-1, Qt-2	

MLP-GDX and RBNN methods were used for daily sediment estimation of Kızılırmak-Söğütlühan sediment observation station. The models were also compared with the sediment rating curve (SRC) of Kızılırmak-Söğütlühan station. The SRC of Kızılırmak-Söğütlühan station is shown in Figure 2.

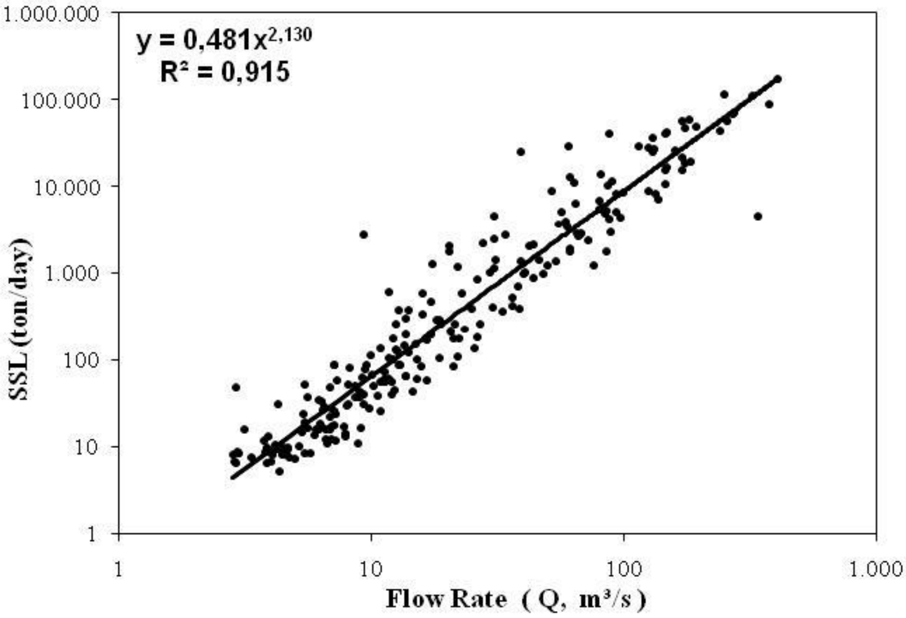

Figure 2. The rating curve of Kızılırmak River-Sogutluhan observation station (Station No: 1535)

Before creating ANN models, the logarithms of the data were taken to eliminate the unit difference in the parameters used in the input and output layer, and then the data was dimensioned between 0 and 1 using the equation below.

$$X_{norm} = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \tag{5}$$

Where; X_{norm}, X_i, X_{min} and X_{max} are the normalized, observed, minimum and maximum values for all parameters, respectively.

3.1. Application of MLP-GDX

The MLP-GDX model is designed as an input layer, two hidden layers and an output layer. The tangent sigmoid and logarithmic sigmoid activation functions were used in the hidden layers and the output layer respectively. In the models, the number of neurons in hidden layers was determined as 1-20 and the learning rate (lr) was determined by trial and error method in the range of 0.1-1. The number of iterations was 1000 and the momentum coefficient (mc) was 0.8. The most successful model was determined according to the highest E_{Nash} value of the test data in the models formed according to ten different input combinations (Table 3).
According to MLP-GDX results, M8 input combination was the most successful model with (4,3,14,1) model structure and 0.9 learning ratio. R^2 = 0.924 and E_{Nash} = 0.907 were obtained in this model.

Table 3. Results of MLP-GDX models

Station Name	Model Name	Model Structure	Leraning rate (lr)	MAE (ton/day)	RMSE (ton/day)	R^2	E_{Nash}
Kızılırmak River-Sögütlühan	M1	(2,1,5,1)	0.9	0.672	0.833	0.912	0.883
	M2	(2,6,15,1)	1	1.438	1.960	0.360	0.352
	M3	(3,9,13,1)	0.1	0.667	0.801	0.922	0.892
	M4	(3,3,3,1)	0.1	1.428	1.904	0.390	0.389
	M5	(4,2,11,1)	0.6	0.680	0.807	0.919	0.890
	M6	(5,2,14,1)	1	0.662	0.821	0.907	0.886
	M7	(3,3,16,1)	0.1	1.515	1.970	0.369	0.345
	M8	**(4,3,14,1)**	**0.9**	**0.595**	**0.744**	**0.924**	**0.907**

	M9	(5,9,13,1)	0.3	1.383	1.784	0.479	0.463
	M10	(6,5,12,1)	0.5	0.667	0.841	0.903	0.881

3.2. Application of RBNN

In RBNN models, three layers are used as input layer, hidden layer and output layer. In the determination of the most successful RBNN model, the number of neurons in the hidden layer was 1-20 and the spread number was examined in the range of 0.01-5 by trial and error method. As a result of the models obtained according to ten different input combinations, the most successful model was determined according to the largest E_{Nash} value of the test data (Table 4).

According to Table 4, the RBNN-M3 model was the most successful model for sediment estimation with the number of spreads 1.24, the number of neurons in the hidden layer 14, R^2= 0.922 and E_{Nash} = 0.903.

Table 4. Results of RBNN models

Station Name	Model Name	Model Structure	MAE (ton/day)	RMSE (ton/day)	R^2	E_{Nash}
Kızılırmak River-Söğütlühan	M1	(2,0.35,3,1)	0.663	0.826	0.912	0.885
	M2	(2,0.1,5,1)	1.469	1.977	0.353	0.341
	M3	**(3,1.24,14.1)**	**0.628**	**0.758**	**0.922**	**0.903**
	M4	(3,0.96,10,1)	1.541	1.944	0.367	0.363
	M5	(4,0.64,17,1)	0.676	0.827	0.907	0.885
	M6	(5,0.52,10,1)	0.687	0.825	0.900	0.885
	M7	(3,0.25,4,1)	1.490	1.945	0.378	0.362
	M8	(4,0.41,5,1)	0.611	0.760	0.918	0.903
	M9	(5,0.32,10,1)	1.510	1.901	0.410	0.391
	M10	(6,0.48,18,1)	0.693	0.849	0.896	0.878

3.3. Comparison of ANN Models and SRC

The performance criteria for the most successful input combination model obtained in ANN models and SRC are given in Table 5.

Table 5. Performance criteria for the most successful ANN models and SRC in testing period

Station Name	Model Name	Model Structure	MAE (ton/day)	RMSE (ton/day)	R^2	E_{Nash}
Kızılırmak River-Söğütlühan	MLP-GDX	M8(4,3,14,1)	0.595	0.744	0.924	0.907
	RBNN	M3(1,1.24,14.1)	0.628	0.758	0.922	0.903
	SRC	-	-1.064-	4.314	0.736	0.435

According to Table 5, MLP-GDX model with M8 input combination was more successful than other models according to all performance criteria. The scatter diagrams and time series for the most successful ANN models and SRC are given in Figure 3.

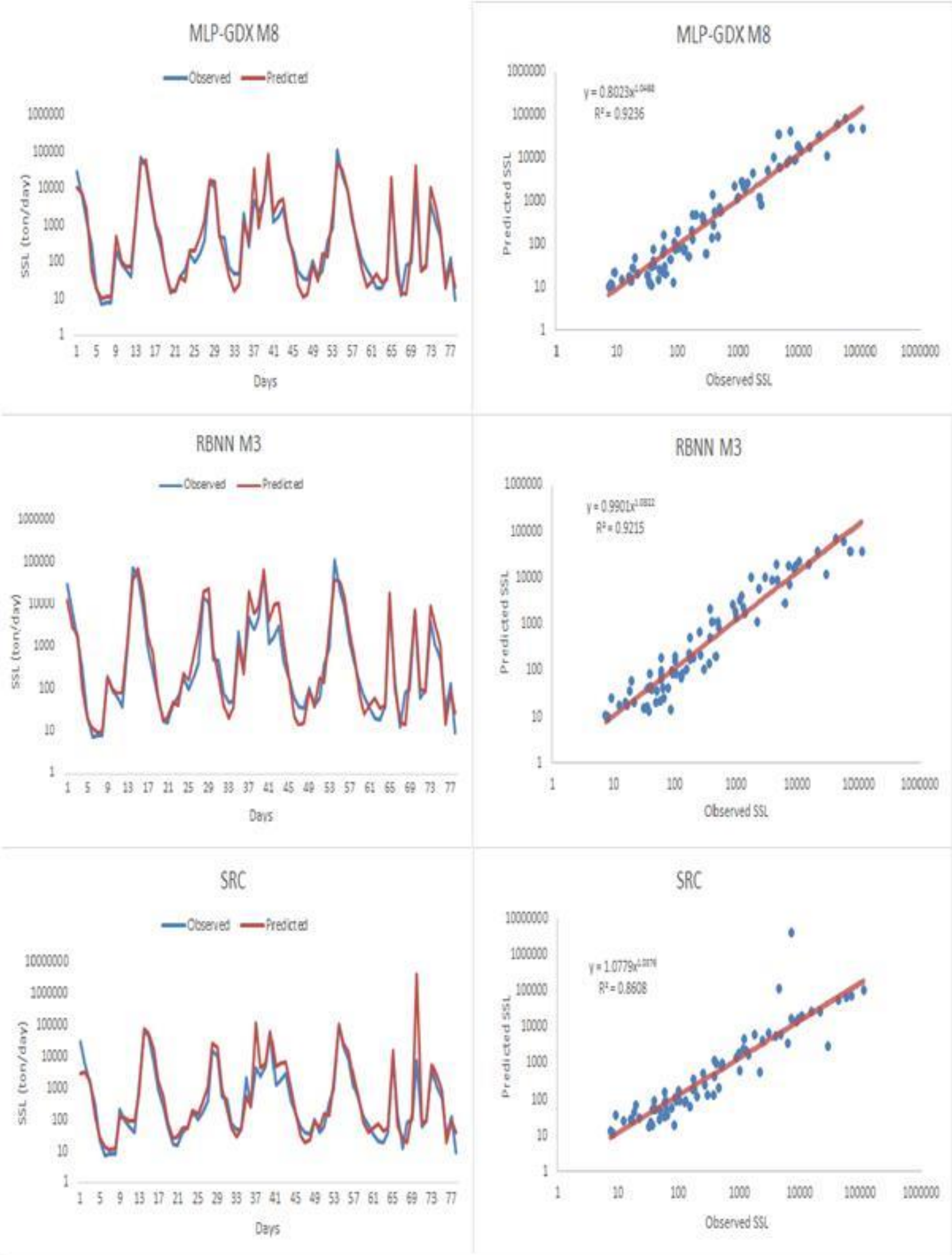

Figure 3. The scatter diagrams and time series for the most successful ANN models and SRC

4. CONCLUSION

Accurate estimation of the sediment amount is very important as it causes a decrease in the economic life of water resources projects constructed at high costs. In this study, the usability of ANN models for daily SSL estimation was investigated. For this purpose, 10 different input combinations consisting of different delay time series of daily flow and SSL values of Kızılırmak River-Sogutluhan sediment observation station (Station No: 1535) were used. ANN models were obtained by using MLP-GDX and RBNN learning algorithms. MLP-GDX and RBNN models showed the most successful performance in M8 and M3 input combinations respectively. The most successful models obtained for each ANN method were also compared with the traditional SRC method. In conclusion, MLP-GDX-M8 (4, 3, 14, 1) model with R^2=0.924, E_{Nash}=0.907, MAE=0.595 ton/day and RMSE=0.744 ton/day was the most successful model with sediment estimation.

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