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Adaptive neuro-fuzzy computing technique for suspended sediment estimation

Ozgur Kisi [a,*], Tefaruk Haktanir [a], Mehmet Ardiclioglu [a], Ozgur Ozturk [a], Ekrem Yalcin [b], Salih Uludag [b]

[a] *Erciyes University, Engineering Faculty, Civil Engineering Department, 38039 Kayseri, Turkey*
[b] *Electrical Power Resources Survey and Development Administration, Ankara, Turkey*

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ABSTRACT

This paper investigates the accuracy of an adaptive neuro-fuzzy computing technique in suspended sediment estimation. The monthly streamflow and suspended sediment data from two stations, Kuylus and Salur Koprusu, in Kizilirmak Basin in Turkey are used as case studies. The estimation results obtained by using the neuro-fuzzy technique are tested and compared with those of the artificial neural networks and sediment rating curves. Root mean squared errors, mean absolute errors and correlation coefficient statistics are used as comparing criteria for the evaluation of the models' performances. The comparison results reveal that the neuro-fuzzy models can be employed successfully in monthly suspended sediment estimation.

1. Introduction

Correct estimation of sediment volume carried by a river is important with respect to channel navigability, reservoir filling, hydroelectric-equipment longevity, river aesthetics, fish habitat and scientific interests. In environmental engineering, if the particles also transport pollutants, the estimation of river sediment load has an additional significance.

McBean and Al-Nassri [26] investigated the uncertainty in suspended sediment curves and they concluded that the practice of using sediment load versus discharge is misleading because the goodness of fit implied by this relation is spurious. They have instead recommended that the regression can be established between discharge and sediment concentration.

Neural networks (NN) have been successfully applied in a number of diverse fields including water resources. In the hydrological forecasting context, recent experiments have reported that artificial neural networks (ANNs) may offer a promising alternative for rainfall–runoff modelling [36,31,9], streamflow prediction [4,30,19,22,6,15], reservoir inflow forecasting [27,13,3], and suspended sediment estimation [12,33,5,20,7,34,1]. Jain [12] used a single ANN approach to establish daily sediment–discharge relationship and found that the ANN model could perform better than the rating curve. Tayfur [33] developed an ANN model for sheet sediment transport and indicated that the ANN could perform as well as, in some cases better than, the physically-based models. Cigizoglu [5] investigated the accuracy of a single ANN in estimation and forecasting of daily suspended sediment data. Kisi [20] used different ANN techniques for daily suspended sediment concentration prediction and estimation and he indicated that multi-layer perceptron could show better performance than the generalized regression neural networks and radial basis function. Cigizoglu and Kisi [7] developed some methods to improve ANN performance in daily suspended sediment estimation. Tayfur and Guldal [34] predicted total suspended sediment from precipitation. Ardiclioglu et al. (2007) compared two different feed-forward backpropagation algorithms in suspended sediment prediction.

Also, fuzzy logic has been used successfully for prediction of suspended sediment during recent years [18,35,21,24,25]. Tayfur [35] used a fuzzy logic algorithm for runoff-induced sediment transport from bare soil surfaces. Kisi [21] developed fuzzy models to estimate daily suspended sediments. He compared the fuzzy estimates with those of the sediment rating curves and found that the fuzzy models performed better than the rating curves. Kisi [24] showed that fuzzy rule-based models using triangular membership functions performs better than the sediment rating curve models in suspended sediment concentration prediction. Lohani [25] used fuzzy logic for deriving stage–discharge–sediment concentration relationships. To the knowledge of the authors, no work has been reported in the literature that investigates the accuracy of neuro-fuzzy (NF) model in monthly suspended sediment estimation.

The main purpose of this study is to analyze the performances of an adaptive NF computing technique for monthly suspended sediment estimation. The monthly streamflow and suspended sediment time series data belonging to two stations in Turkey are used. This paper is organized as follows. Section 2 provides an overview description of the NF, ANN and sediment rating curves

* Corresponding author.
E-mail address: kisi@erciyes.edu.tr (O. Kisi).

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(SRC). Section 3 provides the application of NF, ANN and SRC models on monthly streamflow sediment data and results. Finally, Section 4 provides findings and concluding remarks.

2. Methods

2.1. Artificial neural networks (ANNs)

An ANN has one or more hidden layers, whose computation nodes are correspondingly called hidden neurons of hidden units. A three layered ANN structure is shown in Fig. 1. The hidden neurons intervene between the external input and the network output in some useful manner. The network is enabled to extract higher order statistics by adding one or more hidden layers. In a rather loose sense, despite its local connectivity due to the extra set of synaptic connections and the extra dimension of network interconnections, the ANN acquires a global perspective. The detailed theoretical information about ANN can be found in [11].

The ANN was trained using Levenberg–Marquardt technique here due to that this technique is more powerful and faster than the conventional gradient descent technique [10,23]. The numbers of hidden layer neurons were found using simple trial–error method in all applications. The ANN networks training were stopped after 50 epochs since the variation of error was too small after this epoch.

2.2. Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS was first introduced by Jang [14]. A basic ANFIS is illustrated in Fig. 2. ANFIS is a network structure consisting of a number of nodes connected through directional links. Each node has a node function with adjustable or fixed parameters. Learning or training phase of network is a process to determine parameter values to sufficiently fit the training data. The basic learning rule is the well-known backpropagation method which seeks to minimize sum of squared differences between network's outputs and desired outputs [17].

Depending on the types of inference operations upon "*if-then rules*", most fuzzy inference systems can be classified into three types; Mamdani's system, Sugeno's system and Tsukamoto's system. Mamdani's system is the most commonly used, meanwhile, Sugeno's system is more compact and computationally efficient; the output is crisp, so, without the time consuming and mathematically intractable defuzzification operation, it is by far the most popular candidate for sample-data based fuzzy modelling and it lends itself to the use of adaptive techniques [32].

In first-order Sugeno's system, a typical rule set with two fuzzy IF/THEN rules can be expressed as [29].

$$\textbf{Rule 1}: \text{ If } x \text{ is } A_1 \text{ and } y \text{ is } B_1, \text{ then } f_1 = p_1x + q_1y + r_1 \tag{1}$$

$$\textbf{Rule 2}: \text{ If } x \text{ is } A_2 \text{ and } y \text{ is } B_2, \text{ then } f_2 = p_2x + q_2y + r_2 \tag{2}$$

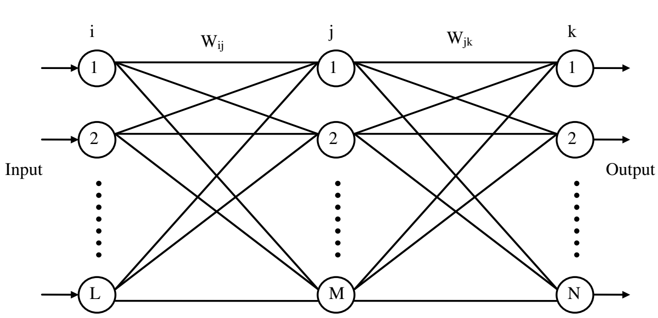

Fig. 1. A three-layer neural network structure.

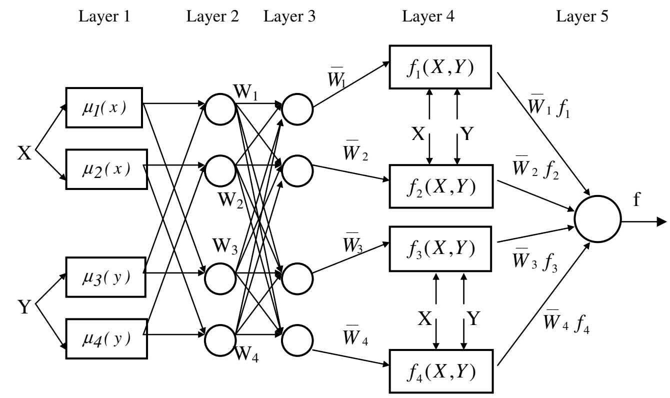

Fig. 2. A basic structure of the ANFIS.

Layer 1: Every node i in this layer is an adaptive node, representing membership functions described by generalized bell functions, e.g.

$$Z_{1,i} = \mu_1(X) = \frac{1}{1 + |(X - c_1)/a_1|^{2b_1}} \tag{3}$$

where X = input to the node and a_1, b_1 and c_1 = adaptable variables known as premise parameters. The outputs of this layer are the membership values of the premise part.

Layer 2: This layer consists of the nodes which multiply incoming signals and sending the product out. This product represents the firing strength of a rule. For example in Fig. 2

$$Z_{2,1} = w_1 = \mu_1(x)\mu_3(y) \tag{4}$$

Layer 3: In this layer, the nodes calculate the ratio of the ith rules firing strength to the sum of all rules' firing strengths

$$Z_{3,1} = \bar{w}_1 = \frac{w_1}{w_1 + w_2 + w_3 + w_4} \tag{5}$$

Layer 4: This layer's nodes are adaptive with node functions

$$Z_{4,1} = \bar{w}_1 f_1 = \bar{w}_1(p_1x + q_1y + r_1) \tag{6}$$

where $\bar{w}_1$ is the output of Layer 3 and $\{p_i, q_i, r_i\}$ are the parameter set. Parameters of this layer are referred to as consequent parameters.

Layer 5: This layer's single fixed node computes the final output as the summation of all incoming signals

$$f = \sum_{i=1}^{n} \bar{w}_i f_i \tag{7}$$

In the present study, the hybrid learning algorithm [14], which combines backpropagation and the least-squares method was used to rapidly train and adapt the fuzzy inference system. If the premise parameters are fixed, the over all output can be given as a linear combination of the consequent parameters. The output f can be written as

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ &= \bar{w}_1(p_1x + q_1y + r_1) + \bar{w}_2(p_2x + q_2y + r_2) \\ &= (\bar{w}_1x)p_1 + (\bar{w}_1y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2x)p_2 + (\bar{w}_2y)q_2 + (\bar{w}_2)r_2 \end{aligned} \tag{8}$$

which is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2, and r_2. Then we have

S set of total parameters,
S_1 set of premise (nonlinear) parameters,
S_2 set of consequent (linear) parameters.

Given values of S_1, we can plug P training data into Eq. (8) and obtain the matrix equation:

$$A\theta = y \tag{9}$$

where θ is an unknown vector whose elements are parameters in S_2, the set of consequent (linear) parameters.

Then the set S_2 of consequent parameters can be identified with the standard least-squares estimator (LSE):

$$\theta^* = (A^TA)^{-1}A^Ty \tag{10}$$

where A^T is the transpose of A and $(A^TA)^{-1}A^T$ is the pseudo-inverse of A if A^TA is non-singular. The recursive least-square estimator (RLS) can also be used to calculate θ^*. More information for ANFIS can be found in related literature [14].

In each application, different number of membership functions is tried and the best one that gives the minimum squared error is selected.

2.3. Sediment rating curve (SRC)

A rating curve consists of an equation or graph, relating sediment discharge or concentration to stream discharge, which can be used to estimate sediment loads from the streamflow record. The sediment rating curves generally represent a functional relationship of the form:

$$S = aQ^b \tag{11}$$

where S is suspended sediment load and Q is stream discharge [28]. a and b values for a particular stream are determined from data by establishing a linear regression between $(\log S)$ and $(\log Q)$. After log-transformation to the arithmetic domain and application of the Ferguson [8] correction factor, the sediment load occurring at a specific discharge can be estimated using the following expression:

$$S = CF \cdot a \cdot Q^b \tag{12}$$

where CF is the log-transformation bias correction factor. Specifically,

$$CF = e^{2.65s^2} \tag{13}$$

where e is the exponential function and s is the standard error of the regression equation. In the applications, first sediment rating curve (Eq. (11)) is denoted as SRC1 and the second one with bias correction factor (Eq. (12)) is denoted as SRC2.

3. Application and results

The monthly streamflow and suspended sediment time series data belonging to Kuylus Station (station no: 1524) and Salur Koprusu Station (station no: 1528), on Kizilirmak River in Kizilirmak Basin, Turkey are used in the study. The locations of the stations are illustrated in Fig. 3. The drainage areas at these sites are 3935 km^2 and 30,589 km^2 and gage datums are 475 and 494 m above sea level for the Kuylus and Salur Koprusu stations, respectively. For these stations, the data were obtained from the report of Turkey General Directorate of Electrical Power Resources Survey and Development Administration.

In each application, two sets of data are used. The first data set is used to train the NF and ANN models, and is referred to as the training set. The second data set is used to determine how well the trained models performed. For the Kuylus Station, 180 monthly data (80% of the whole data) are used for training and the remaining 45 months (20% of the whole data) for testing. For the Salur Station, 226 monthly data are used for training and the remaining 57 months for testing. The training and test data periods are March 1981–December 1995 and January 1996–September 1999 for the Kuylus Station, respectively. For the Salur Koprusu, the data of December 1972–September 1992 and October 1992–April 1997 are respectively used for the training and testing. The data are not continuous in both gauging sites, since the observations for some months in-between are not available for technical reasons. This decreases the models' prediction performances.

The statistical parameters of the streamflow and sediment data for the Kuylus and Salur Koprusu stations are given in Table 1. In the table, the x_{mean}, S_x, C_v, C_{sx}, x_{max} and x_{min} denote the mean, standard deviation, variation coefficient, skewness, maximum and minimum, respectively. It can be seen from the skewness coefficients in the eighth column of the table (Table 1) that the streamflow and sediment data show scattered distribution. The variation coefficients are also not low for the both stations. The maximum–mean ratio (x_{max}/x_{mean}) for sediment series in the training period is also quite high (55 and 11 for the Kuylus and Salur Koprusu, respectively). All these statistics indicate the complexity of the discharge–sediment phenomenon. In the training sediment data, minimum and maximum values fall in the ranges 413 t–213,214 t for the Salur Koprusu Station. However, the maximum of the testing set of the sediment data of the Salur Koprusu Station is 348,506 t which is much higher than the corresponding training set's value. This may cause some extrapolation difficulties in prediction of high sediment values of the Salur Koprusu Station [6].

Seven different neuro-fuzzy (NF) models are established to estimate suspended sediment from streamflow. Each NF model has different number of membership functions (between 2 and 8). The triangle and Gaussian membership functions are tried for each NF model. The NF models are compared with two different ANN and SRC models. Four different program codes, including neural networks and fuzzy logic toolboxes, are written in MATLAB language for the simulations of NF, ANN, SRC1 and SRC2 techniques. SRC1 and SRC2 formulas obtained for the Kuylus Station (Eqs. (14) and (15)) and Salur Koprusu Station (Eqs. (16) and (17)) respectively are:

$$S = 1.8617 \cdot Q^{2.0126} \tag{14}$$

$$S = 0.8617CF \cdot Q^{1.3549} \tag{15}$$

$$S = 1.4196 \cdot Q^{13.0897} \tag{16}$$

$$S = 0.4196CF \cdot Q^{3.0555} \tag{17}$$

CF values are calculated as 1.4774 and 1.4476 in Eqs. (15) and (17), respectively.

The root mean square errors (RMSE), mean absolute errors (MAE) and correlation coefficient (R) statistics are used as the comparing criteria in these applications. The RMSE, MAE and R statistics are denoted as below

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Yi_{\mathrm{observed}} - Yi_{\mathrm{predicted}})^2} \tag{18}$$

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{N}|Yi_{\mathrm{observed}} - Yi_{\mathrm{predicted}}| \tag{19}$$

in which N is the number of data, Y_i is the sediment concentration.

The correlation coefficient between two variables, say x and y, whose n pairs are available, can be calculated by

$$R = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2}} \tag{20}$$

where the bar denotes the mean of the variable. The R shows the degree which two variables are linearly related to. Different types of information about the predictive capabilities of the model are measured through MSE and MAE. The MSE sizes the goodness of the fit

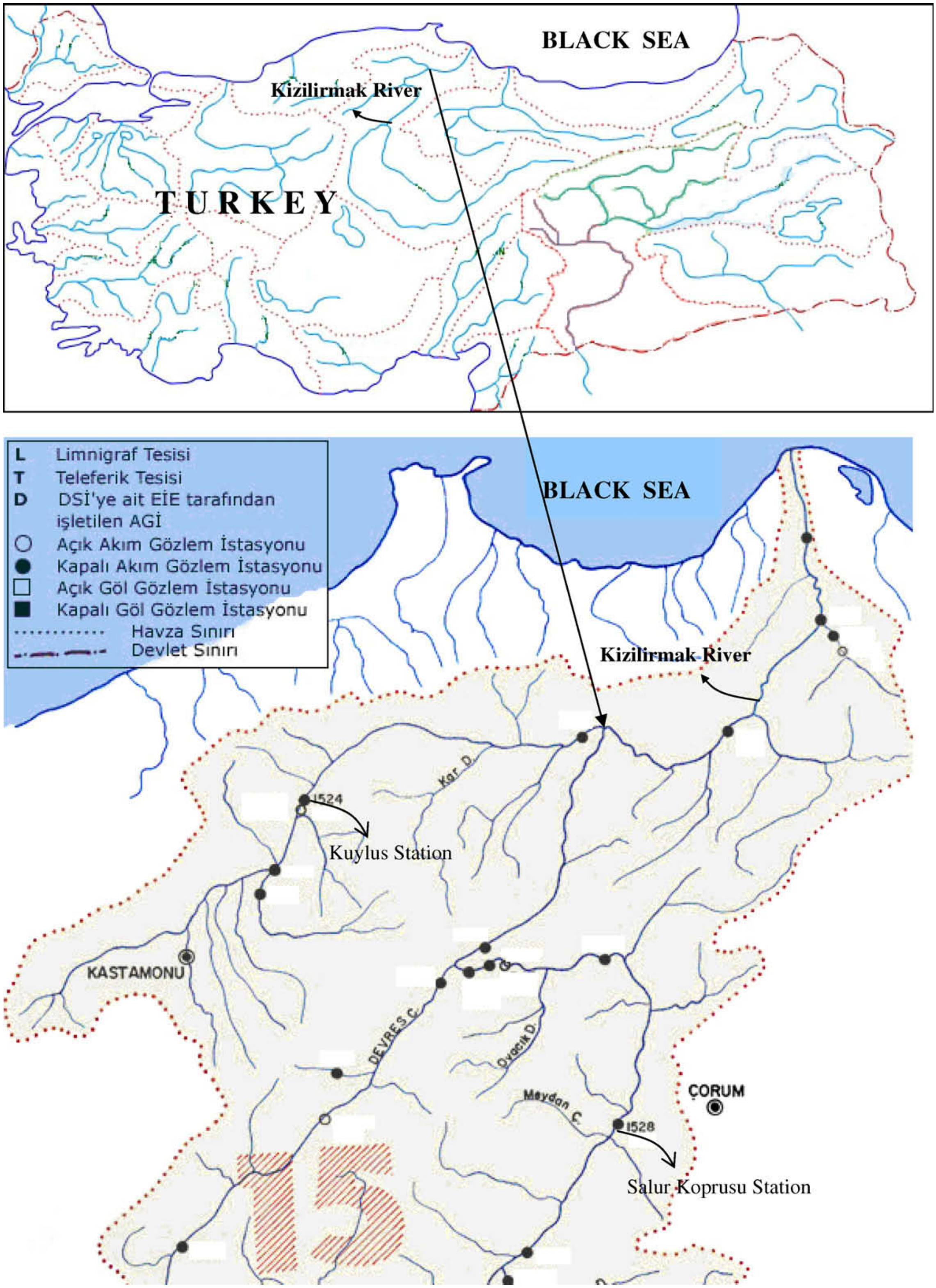

Fig. 3. The location of the Kuylus (station no: 1524) and Salur Koprusu (station no: 1528), on Kizilirmak River in Kizilirmak Basin.

related to high sediment values whereas the MAE measures a more balanced perspective of the goodness of the fit at moderate sediments [16].

The RMSE, MAE and R statistics of NF, ANN and SRC models for the Kuylus Station are given in Table 2. In this table *trimf* and *gaussmf* denote the triangle and Gaussian membership functions, respectively. NF(2,*trimf*) denotes a NF model having two triangle membership functions. The ANN1 shows an ANN model whose hidden and output layers having logarithm sigmoid activation function. The ANN2 model uses linear function in its output layer. The ANN1(6) denotes an ANN model comprising 6 hidden nodes. The hidden layer node numbers of each ANN model are determined

Table 1
The statistical parameters of data set for the stations

Data set	Station	Basin area (km^2)	Data type	x_{mean}	S_x	C_v (S_x/x_{mean})	C_{sx}	x_{max}	x_{min}	$\frac{x_{max}}{x_{mean}}$
Training	Kuylus	3935	Flow (m^3/s)	17.7	22.5	1.27	3.71	174	0.64	9.88
			Sediment (t)	1708	7917	4.63	9.82	93,903	0.48	54.9
	Salur Koprusu	30,589	Flow (m^3/s)	117	64.1	0.55	1.53	392	14.9	3.36
			Sediment (t)	18,719	28,505	1.52	3.36	213,214	413	11.4
Testing	Kuylus	3935	Flow (m^3/s)	15.6	15.9	1.03	1.81	65.8	0.31	4.23
			Sediment (t)	1002	2744	2.74	4.53	16,344	1.28	16.3
	Salur Koprusu	30,589	Flow (m^3/s)	108	66.9	0.62	2.17	388	41.8	3.59
			Sediment (t)	22,503	52,824	2.35	4.86	348,506	1157	15.5

Table 2
The test performances of the models in suspended sediment estimation – Kuylus Station

Model	RMSE (*t*)	MAE (*t*)	*R*
NF(2,*trimf*)	1763	591	0.768
NF(3,*trimf*)	1746	582	0.775
NF(4,*trimf*)	1965	831	0.742
NF(5,*trimf*)	1771	639	0.760
NF(6,*trimf*)	**1720**	600	**0.785**
NF(7,*gaussmf*)	1822	571	0.764
NF(8,*gaussmf*)	1809	**567**	0.769
ANN1(6)	1823	**567**	0.766
ANN2(6)	1823	577	0.762
SRC1	2017	573	0.777
SRC2	2021	574	0.777

after trying various network structures since there is no theory yet to tell how many hidden units are needed to approximate any given function.

It can be seen from Table 2 that the NF(6,*trimf*) model having six triangle membership functions has the lowest RMSE (1720 t) and the highest *R* value (0.785). It can be said that NF(6,*trimf*) model estimates high sediment values better than the ANN and SRC models. However, the NF(8,*gaussmf*) and ANN1(6) model perform better than the NF(6,*trimf*) model from the MAE viewpoint. ANN1 and ANN2 models show almost same accuracy and their performances seem to be better than the SRC models.

The scatter plots of observed suspended sediments and the estimates of the NF(6,*trimf*), ANN1, SRC1 and SRC2 models are given in Fig. 4. As can be seen from this figure, the fit line of the NF closer to the exact (45°) line with a higher *R* value than those of the ANN1, SRC1 and SRC2 models. The logarithm scaled scatter plots are also provided in Fig. 5 for better representation. As seen from the scatter plots, the NF model estimates are less scattered in relative to the other models.

The estimation of total sediment load is also considered for comparison due to its importance in reservoir management. The NF model predicts the observed total sediment load 45,098 t as 41,872 t, with an underestimation of 7%, while the YSA1, SRC1 and SRC2 compute as 40,720 t, 26,880 t and 26736 t, with underestimations of 10%, 40% and 41%, respectively. YSA1 model also seems to be much better than the SRC models in estimating total sediment load.

The results are also tested by using one way analysis of variance (ANOVA) and *t*-test for verifying the robustness (the significance of differences between the model estimates and observed values) of the models. Both tests are set at a 95% significant level. Namely, differences between observed and estimated values are considered significant when the resultant significance level (p) is lower than the 0.05 by use of two-tailed significance levels. The statistics of the tests are given in Table 3. The NF model yields small testing values (0.022 and 0.147) with a high significance level (0.884) for the ANOVA and *t*-test, respectively. According to the test results,

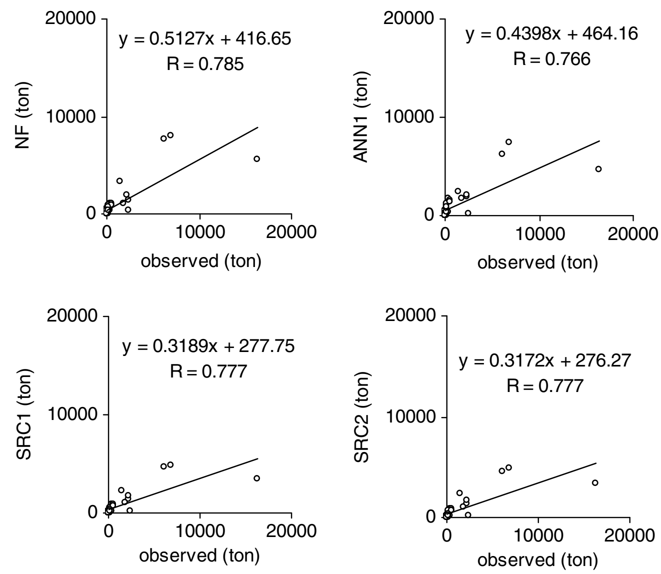

Fig. 4. Plotting of prediction performances for the test period using NF, ANN1, SRC1 and SRC2 – Kuylus Station.

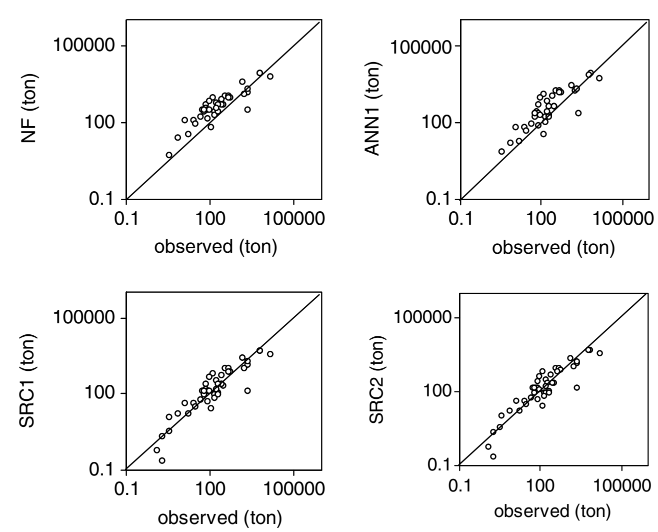

Fig. 5. Plotting of prediction performances for the test period using NF, ANN1, SRC1 and SRC2 (logarithm scaled) – Kuylus Station.

the NF seems to be more robust (the similarity between the observed sediments and NF estimates are significantly high) in suspended sediment estimation than the others. The ANN1 model is also better than the SRC1 and SRC2.

Table 3
Analysis of variance and t-test for suspended sediment estimation in test period – Kuylus Station

Method	ANOVA		t-Test	
	F-statistic	Resultant significance level	t-Statistic	Resultant significance level
NF	0.022	0.884	0.147	0.884
ANN1	0.043	0.837	0.206	0.837
SRC1	0.839	0.362	0.916	0.364
SRC2	0.853	0.358	0.924	0.359

The RMSE, MAE and R statistics of NF, ANN and SRC models for the Salur Koprusu Station are represented in Table 4. Table 4 reveals that the NF(8,*trimf*) having eight triangle membership functions performs better than the other models from the RMSE viewpoint. However, the lowest MAE value belongs to NF(5,*trimf*) model. SRC1 and SRC2 models have the highest R value. Note that the R term provides information for linear dependence between observations and corresponding estimates. Therefore, it is not always expected that R is in agreement with performance criteria such as the RMSE. For example, in the case of two time series such as ($X_i = 1,2,3,\ldots,10$; $Y_i = 20,40,60,\ldots,200$) the R between these two series is equal to 1 whereas the RMSE value is quite high. An R value equal to 1 does not guarantee that a model captures the behavior of the investigated time series. An ANN1 model seems to be better than the SRC models according to the RMSE and MAE criteria. In the study the main model performance criterion is the RMSE. The best model is selected by considering this criterion.

The estimates of the NF(8,*trimf*), ANN1, SRC1 and SRC2 models are shown in Fig. 6, in the form of scatter plot. From Fig. 6, it can be said that the fit line of the NF model closer to the 45° line than those of the other models. SRC2 provides the worst estimates. Fig. 7 shows the logarithm scaled scatter plots of each model. The accuracy of NF model seems to be better than the ANN1 and SRC in estimation of high sediment values. The underestimations of the SRC2 model are obviously seen.

The NF model predicts the total sediment load as 1,094,262 t instead of measured 1,219,456 t, with an underestimation of 10%, while the YSA1, SRC1 and SRC2 compute as 902,693 t, 608,055 t and 205,459 t, with underestimations of 26%, 50% and 83%, respectively. NF estimate is closest to the observed one. The statistics of the ANOVA and t-test are given in Table 5. The NF model seems to be more robust than the ANN1 and SRC models in estimation of suspended sediment. The ANN1 also seems to be much better than the SRC models.

To summarize, the NF and ANN1 models seem to be more adequate than the SRC in modelling suspended sediment. Suspended sediment estimation requires nonlinear mapping. The SRC models are not adequate in view of the complexity of the problem since it assumes linear relationship between $\log S$ and $\log Q$ values. Such models require that the variables are normally distributed. It is evident from Table 1 that the streamflow and sediment data have

Table 4
The test performances of the models in suspended sediment estimation – Salur Koprusu Station

Model	RMSE (t)	MAE (t)	R
NF(2,*trimf*)	40,827	15,663	0.752
NF(3,*gaussmf*)	41,667	16,000	0.728
NF(4,*trimf*)	41,570	15,889	0.748
NF(5,*trimf*)	42,522	**15,658**	0.640
NF(6,*gaussmf*)	43,429	15,947	0.573
NF(7,*gaussmf*)	41,709	16,303	0.628
NF(8,*trimf*)	**39,641**	15,926	0.686
ANN1(2)	41,504	15,897	0.740
ANN2(6)	48,563	16,809	0.388
SRC1	46,239	16,514	**0.760**
SRC2	53,105	19,004	**0.760**

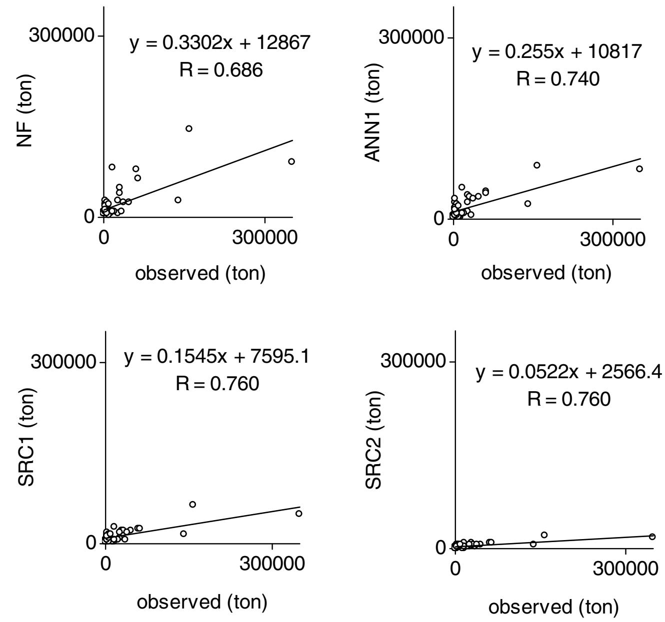

Fig. 6. Plotting of prediction performances for the test period using NF, ANN1, SRC1 and SRC2 – Salur Koprusu Station.

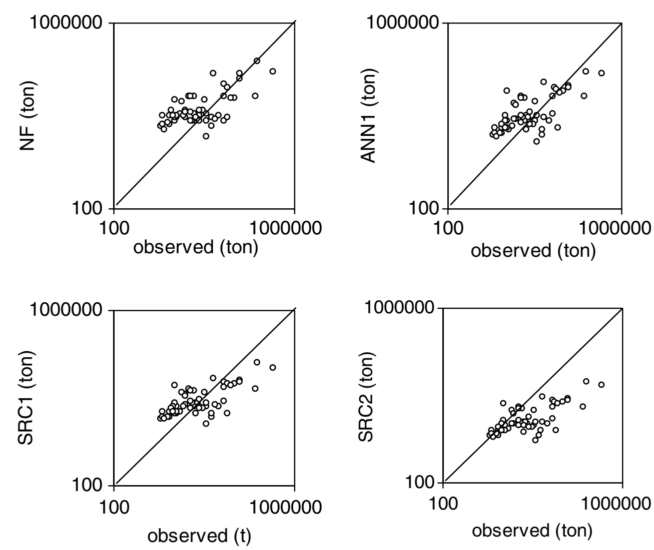

Fig. 7. Plotting of prediction performances for the test period using NF, ANN1, SRC1 and SRC2 (logarithm scaled) – Salur Koprusu Station.

Table 5
Analysis of variance and t-test for suspended sediment estimation in test period – Salur Koprusu Station

Method	ANOVA		t-test	
	F-statistic	Resultant significance level	t-Statistic	Resultant significance level
NF	0.081	0.777	0.284	0.777
ANN1	0.648	0.422	0.805	0.423
SRC1	2.563	0.112	1.601	0.115
SRC2	7.157	0.009	2.675	0.010

scattered distribution (see C_{sx} values in Table 1). The main advantages of using ANNs are their flexibility and ability to model nonlinear relationships. Mathematically, an ANN may be treated as an universal approximator [2]. This technique has already become a prospective research area with great potential due to the ease of application and simple formulation. On the other hand, the NF models combine the linguistic representation of a fuzzy system with the learning ability of the ANN. Therefore, they can be trained to perform an input/output mapping, just as with an ANN, but with the additional benefit of being able to provide the set of rules on which the model is based. This gives further insight into the process being modelled [29]. In general, the NF model can be considered to be relatively superior to the ANN and SRC models. This observation would be of much use in hydrological modelling studies where estimates of sediment values are not available. The model can be integrated as a module in general hydrological analysis models.

4. Conclusions

The potential of an adaptive neuro-fuzzy computing technique in monthly suspended sediment estimation has been illustrated in this paper. The estimates of the NF models were compared with those of the ANN and SRC models. Based on the comparison results, the NF technique was found to perform better than the other models. The accuracy of the NF model in total sediment load estimation was also investigated and results were compared with those of the ANN and SRC models. Comparisons revealed that the NF model had the best accuracy in total sediment load estimation. The ANN1 model also gave better estimates than the SRC1 and SRC2.

In the present study, the ANFIS model was compared with the ANN and SRC models using the standard backpropagation algorithm. If the other training algorithms (conjugate gradient, quasi-Newton etc.) were used, the results from the ANFIS model may turn out to be better. The estimation of monthly suspended sediment is very difficult, and there is room for much improvement.

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