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ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS APPLICATION FOR ESTIMATING SUSPENDED SEDIMENT LOAD

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ABSTRACT The transport of sediment load in rivers is important with respect to pollution, channel navigability, reservoir filling, hydroelectric-equipment longevity, fish habitat, river aesthetics and scientific interest. Direct measurement of the suspended sediment load in rivers is very expensive and can not be conducted for all river gauge stations. Furthermore, sediment transport equations do not agree with each other and require many detailed data. In this study, because of the complexity of the phenomenon, artificial intelligence method adaptive neuro-fuzzy inference systems (ANFIS) which is the powerful tool for input-output mapping are used to estimate daily suspended sediment load. The daily streamflow and suspended sediment data collected from Coruh River, Oltu Stream, Iyi Stream and Harsit Stream Stations in the Black Sea Region of Turkey are used as case studies. The sediment rating curve (SRC) and multi-linear regression (MLR) are also applied to the same data. The ANFIS results are compared with the SRC and MLR models. The root mean square errors (RMSE) and determination coefficient (R2) performance functions are used to evaluate the adequacy of the models. Comparison results showed that the ANFIS results are superior to the other methods.

INTRODUCTION

Prediction of sediment load are required in a wide spectrum of problem such as design of the dead volume of a dam, sediment transport in the river, design of stable channels, estimation of aggradation and degradation at bridge piers, prediction of sand and gravel mining effects on river-bed equilibrium, determination of the environmental impact assessment and dredging needs (Nakato, 1990 ; McBean et al. 1988). Also sediment is a major pollutant and a carrier of nutrients, pesticides, and other chemicals (Lopez et al. 2001). The suspended sediment load of the stream is generally determined from direct measurement of the sediment load or from sediment transport equations. Although direct measurement is most reliable method, it is very expensive and the sediment measurement can not be done for as many streams as the measurement of water discharge. On the other hand, most of the sediment transport equations require detailed information on the flow and sediment characteristics (Ozturk et al. 2001). Recently, because of these problems, researchers are looking for simpler, cheaper and easier methods to obtain a relationship between sediment load and water discharge and they are begining to use nonlinear models such as artificial intelligence techniques to solve nonlinear problems. In this paper, it seems necessary to use nonlinear models such as adaptive neuro-fuzzy inference system (ANFIS), which is developed for estimating daily sediment load for Coruh River, Oltu Stream, Iyi Stream and Harsit Stream Stations in the

Black Sea Region of Turkey. These techniques are also suited to the complex non-linear models and cope with these difficulties and complexities. The artificial neural networks (ANNs) approach has been applied to many branches of science. The approach is becoming a strong tool for providing civil and environmental engineers with sufficient details for design purposes and management practices. Motivated by successful applications in modeling nonlinear system behavior in a wide range of areas, ANNs have been applied in hydrology and hydraulics. ANNs have been used for rainfall-runoff modeling, flow predictions, flow/pollution simulation, parameter identification, and modeling nonlinear/ input-output time series (ASCE, 2000a). Nagy et al. (2002) estimated that the natural sediment discharge in rivers in terms of sediment concentration by ANN model gives better results compared to several sediment transport formulas. Dogan et al. (2005) used artificial neural network (ANN) and fuzzy logic (FL) for predicting monthly suspended sediment load of Sakarya River in Turkey. It was observed that the FL gave better results than the ANN model. In this paper it seems necessary that nonlinear models such as adaptive neuro-fuzzy inference system (ANFIS), is used to develop suspended sediment load estimation. This technique is also suited the complex non-linear models and cope with these difficulties and complexity. Comparison results revealed that the ANFIS model performs better than the other techniques in estimation of daily suspended sediment load.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS)

Jang (1993) introduced architecture and learning procedure for the FIS that uses a neural network learning algorithm for constructing a set of fuzzy if-then rules with appropriate membership functions (MFs) from the specified input–output pairs. This procedure of developing a FIS using the framework of adaptive neural networks is called an adaptive neuro fuzzy inference system (ANFIS). There are two methods that ANFIS learning employs for updating membership function parameters: 1) backpropagation for all parameters (a steepest descent method), and 2) a hybrid method consisting of backpropagation for the parameters associated with the input membership and least squares estimation for the parameters associated with the output membership functions. As a result, the training error decreases, at least locally, throughout the learning process. Therefore, the more the initial membership functions resemble the optimal ones, the easier it will be for the model parameter training to converge. Human expertise about the target system to be modeled may aid in setting up these initial membership function parameters in the FIS structure. ANFIS architecture is shown in Figure 1.

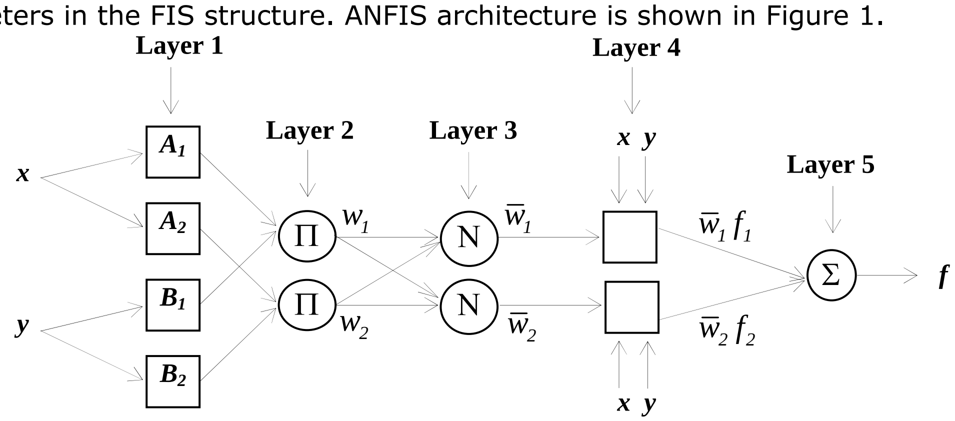

Figure-1 ANFIS architecture

For instance, assume that the FIS has two inputs x and y and one output z. For the first order Sugeno fuzzy model, a typical rule set with two fuzzy if-then rules can be expressed as:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 y + r_1$, (1)

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 y + r_2$, (2)

where A_1, A_2 and B_1, B_2 are the MFs for inputs x and y, respectively, p_1, q_1, r_1 and p_2, q_2, r_2 are the parameters of the output function. The functioning of the ANFIS is described as:

Layer 1: Every node in this layer produces membership grades of an input parameter. The node output $O_{1,i}$ is explain by,

$O_{1,i} = \mu A_i(x)$, for $i = 1, 2,$ or (3)

$O_{1,i} = \mu B_{i-2}(y)$, for $i = 3, 4$ (4)

where x (or y) is the input to the node i; A_i (or B_{i-2}) is a linguistic fuzzy set associated with this node. $O_{1,i}$ is the MFs grade of a fuzzy set and it specifies the degree to which the given input x (or y) satisfies the quantifier. MFs can be any functions that are Gaussian, generalized bell shaped, triangular and trapezoidal shaped functions. A generalized bell shaped function can be selected within this MFs and it is described as:

$$\mu_{Ai}(x) = \frac{1}{1 + \left| \frac{x - c_i}{a_i} \right|^{2b_i}} \tag{5}$$

where $\{a_i,\ b_i,\ c_i\}$ is the parameter set which changes the shapes of the MF degree with maximum value equal to 1 and minimum equal to 0.

Layer 2: Every node in this layer is a fixed node labeled Π, whose output is the product of all incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x)\,\mu_{Bi}(y),\ i = 1,\ 2 \tag{6}$$

Layer 3: The *i*th node of this layer, labeled N, calculates the normalized firing strength as, $O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2},\ i = 1,\ 2$ (7)

Layer 4: Every node *i* in this layer is an adaptive node with a node function,

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i \left(p_i x + q_i y + r_i \right), \tag{8}$$

where $\overline{w}_i$ is the output of layer 3 and $\{p_i,\ q_i,\ r_i\}$ is the parameter set of this node.

Layer 5: The single node in this layer is a fixed node labeled Σ, which computes the overall output as the summation of all incoming signals:

Overall output = $O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\Sigma_i w_i f_i}{\Sigma_i w_i}$ (9)

The ANFIS estimates are compared with those of the multiple linear regression (MLR) and sediment rating curve (SRC) techniques in Table 1. It can be obviously seen from this table that the ANFIS model has the lowest RMSE and the highest R^2 values. For the

Harsit Stream, the MLR provides better estimates than the SRC. However the SRC shows better performance than the MLR for the other three stations. The estimation of total sediment load was also considered for comparison, owing to its importance in reservoir management. For the Harsit Stream, the ANFIS and MLR predicted the total sediment amount of 133151 ton as 123872 and 106225 ton, with underestimations of 7% and 20.2%, respectively, while the SRC resulted in 155609 ton, with an overestimation of 16.9%. The ANFIS estimate is closest to the observed one. The SRC model is ranked as the second best.

Table -1. The comparison of models in terms of the RMSE and R^2 statistics in test period

Models	Harsit Stream		Iyi Stream		Coruh River		Oltu Stream	
	RMSE ton day^{-1}	R^2	RMSE ton day^{-1}	R^2	RMSE ton day^{-1}	R^2	RMSE ton day^{-1}	R^2
ANFIS	**1371**	**0.970**	**522**	**0.980**	**1051**	**0.996**	**228**	**0.998**
MLR	4593	0.859	3447	0.473	8536	0.918	2442	0.862
SRC	8173	0.669	3177	0.901	5487	0.831	2121	0.989

CONCLUSION

In this study ANFIS soft computing technique was used for modeling the relationship between daily water discharge and suspended sediment load. Appropriate models were developed by scrutinizing their performance degrees. It was observed that the ANFIS model significantly outperforms the MLR and SRC models. A significant improvement is observed for the ANFIS in the peak suspended sediment load estimation compared to other models. The results of the study are highly encourages and suggests that ANFIS approach is reasonable for modeling suspended sediment prediction.

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