Investigation of the Multi Layer Perceptron, Fuzzy logic and Neuro-Fuzzy for Estimating of Suspended load

A. Salajegheh, A. Fathabadi, S. Salajegheh and M. Sanjari

Abstract—There are different hydrologic and hydraulic methods for estimating of the suspended load but using sediment rating curve is the most common one for estimation. Relation between sediment and water discharges supposed linear in this method but nonlinearity and complexity of relation cause low level accuracy of linear modeling and it couldn't model the equation perfectly. This paper considers estimation and modeling of sediment-discharge nonlinearity using Artificial Intelligence (Multi layer Perceptron, Fuzzy logic and Neuro-Fuzzy). Suspended load of Brandywine Creek watershed in Chester County, Pa at Chadds Ford station estimated using these methods. Dataset divided in three different parts of training, testing and validation. Four kind of different compounds of water and sediment dataset used for learning process of model as inputs. The results show that these methods could model nonlinear relationship between water and sediment discharge accurately. The comparison of MLP, FL and NF methods and classic ones (sediment rating curve, regression) show that MLP had better application than Classic ones and hybrid Neuro-Fuzzy modeling shows the best accuracy among all methods.

Keywords—suspended load, Feedforward Neural Network, Fuzzy logic, Neuro-Fuzzy, Brandywine Creek watershed.

I. INTRODUCTION

Estimating and prediction of suspended sediment load (SSL) has an important role in the field of river engineering, dam designing, environmental problems, watersheds and water resources management. There are different hydrological models to estimate suspended load but complexity of rainfall runoff processing leads some restriction and problems in this field [11]. Because of simplicity, Hydrologic method often used for estimation of the suspended load and the best methodology for determination of suspended load using hydrologic one is direct measurement. It needs complete sediment concentration and flow discharge data records of river. In direct measurement, often these data don’t exist completely because of some problems such as expert and facility shortage, high price of data collection [1]. So the indirect methods included interpolation and extrapolation used in the most time as sediment rating curve. A sediment rating curve is graph or equation, relating sediment discharge or concentration to stream discharge. Such a relationship is usually established by a regression analysis, and the curves are generally expressed in the form of a power equation [3]-[10]. Sediment concentration for water discharge in the rising stage of hydrograph are more than the falling stage that caused nonlinear relation between sediment and discharge and sediment rating curve couldn't model this relation [3]. According to this complexity that caused nonlinear relation between flow and sediment discharge, researchers try to found other methods to make more accurate modeling. Artificial Neural Networks (ANNs), fuzzy logic and Adaptive Neuro-fuzzy inference system (ANFIS) are three well-known models for nonlinear input–output mapping and have been successfully applied in a number of diverse fields, including water resources. Recent reviews reveal that more than 90% of the applications of artificial neural networks (ANNs) for water resources variables modeling is the standard feedforward Neural Networks [4]. Estimation of suspended load using Multilayer Perceptron Neural Network consider by Cigizoglu [2]. Results shows that the ANN has better ability to estimation of suspended load in comparison of sediment rating curve. Dogan and et al [6] investigated the efficiency of the Fuzzy logic method and ANN for lower Sakarya River. They found that the fuzzy logic gives better estimate than neural network. Also Kisi and et al [10] show that the fuzzy logic model could have better accuracy than sediment rating curve for estimating of suspended load. Kisi [9] investigated the abilities of ANFIS and neural network (NN) approaches to model the stream flow–suspended sediment relationship for two stations—Quebrada Blanca station and RioValenciano station—operated by the US Geological Survey. Results showed that ANFIS model had better application than the other technique. Cobaner [3] developed an adaptive neuro-fuzzy to estimate suspended sediment concentration. Result showed that neuro-fuzzy model had better performance than the other models (generalized regression neural networks (GRNN), radial basis neural networks (RBNN) and multilayer perceptron (MLP) and two different sediment rating curves (SRC)) in daily suspended sediment concentration estimation. Rajaee [12] considered artificial neural networks (ANNs), neuro-fuzzy (NF), multi linear regression (MLR) and

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conventional sediment rating curve (SRC) models for time series modeling of suspended sediment concentration (SSC) in Little Black River and Salt River gauging stations in the USA. Results revealed that ANN and NF models had better performance than MLR and SRC methods.

In this paper, According to the nonlinear relation between flow and sediment discharge and non-efficiency of the sediment rating curve for estimating of the suspended load, estimation of suspended load using Neural Network, Fuzzy logic, Neuro-Fuzzy and Classic methods in Brandywine Creek watershed considered and then compare these methods with each others to determinate the efficiency of models.

II. MATERIAL AND METHODS

A. Study area

According to the daily sediment and flow data records available in Brandywine Creek watershed, this basin selected for research (Fig. 1). Brandywine Creek located in the Piedmont physiographic province and characterized by pronounced heterogeneity in land surface properties. In this paper, daily data of Chodds Ford gauging station that located in longitude of 75 35 37 W and latitude of 39 52 11 N consider for sediment load modeling. All Data download from USGS official website (http://webserver.cr.usgs.gov/sediment).

B. Multi Layer Perceptron

ANN is a simulation method that inspired by biological nerve system. Multi layer Perceptron (MLP) using back-propagation is the most common ANN used in solving of various engineering problems. In the standard MLP, the neurons are arranged in the input, hidden and output layers. In artificial neuron the scalar p and a are input and output from neuron respectively (Fig. 2). The scalar input p is transmitted through a connection that multiplies its strength by the scalar weight w, to form the product wp, again a scalar. Here the weighted input wp is the only argument of the transfer function f, which produces the scalar output a. The neuron on the right has a scalar bias, b, the bias as simply being added to the product wp as shown by the summing junction or as shifting the function f to the left by an amount b. The bias is much like a weight, except that it has a constant input of one. The transfer function net input n, again a scalar, is the sum of the weighted input wp and the bias b. This sum is the argument of the transfer function [5].

The number of neurons in input and output layer equals to number input and output, the most important problem in this network is determined the best number of hidden layer and the number of neurons in hidden layers that for this, showed that network with one hidden layers and with sigmoid function in hidden layers and linear function on output layer with enough neuron in hidden layer can estimate any function. In this study network with one hidden layer that have sigmoid function in hidden layer and linear function in output layer that number neurons were determined by trail and error procedure were considered. And levenberg–maquaret learning algorithm is used for its speed and effectiveness.

C. Fuzzy logic

Fuzzy logic is suitable way to solving the nonlinear systems that introduced by zade (1965). Fuzzy logic (FL) is almost synonymous with the theory of fuzzy sets, a theory which relates to classes of objects with smooth boundaries in which membership is a matter of degree. Fuzzy logic is a convenient way to map an input space to an output space. Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. Each fuzzy inference system contains 3 parts: fuzzier, fuzzy operator and defuzzier.

D. ANFIS

The Adaptive Neuro-fuzzy inference system (ANFIS) [7], is universal approximate which has capability in the approximation of any real continuous function on a compact set to any degree of accuracy [8]. Its combination of the least-squares method and the back propagation gradient descent for training of FIS membership function parameters. As Figure 3 shows, the ANFIS model includes 5 layers that are summarized below. The output of the ith node in layer l is denoted as $O_{il}$.

Layer 1: Every node i in this layer is an adaptive node with node function:

$$O_{il} = \mu_{A_i}(x) \quad \text{For } i = 1, 2, \text{ or }$$

$$O_{il} = \mu_{B_i}(y) \quad \text{For } i = 3, 4$$

where x (or y) is the input to the ith node and $A_i$ (or $B_i$) is a linguistic label (such as “low” or “high”) associated with this node. $O_{il}$ is the membership grade of a fuzzy set A ($=A_1$, $A_2$, $B_1$, or $B_2$) and it specifies the degree to which the given input x (or y) satisfies the quantifier A. The membership functions for A and B can be described by generalized bell functions, equation (1)

$$\mu_{A_i}(x) = \frac{1}{1 + [(x-c)/a_i]^{2b_i}}$$

Where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership functions on linguistic label $A_i$. In fact, any continuous and piecewise differentiable functions, such as commonly used triangular-shaped membership functions, are also qualified candidates for node functions in this layer. Parameters in this layer are referred to as premise parameters. The outputs of this layer are the membership values of the premise part.

Layer 2: This layer consists of the nodes labeled $\Pi$ which multiple all the incoming signals and send it out. For example,

$$O_{2j} = w_j = \mu_{A_i}(x)\mu_{B_i}(y), i = 1, 2.$$ (2)

Each node output represents the firing strength of a rule.

Layer 3: In this layer, the nodes labeled $\Sigma$ calculates the ratio of the ith rule’s firing strength to the sum of all rules’ firing strengths
The outputs of this layer are called normalized firing strengths. 

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

\[ O_{4,i} = w_i f_i = w_i (p_i x + q_i y + r_i) \]  

(4)

Where \( w_i \) is the output of, and \{pi, qi, ri\} are the parameter set. Parameters of this layer are referred to as consequent parameters.

Layer 5: This layer’s single fixed node labeled \( \Sigma \) computes the final output as the summation of all incoming signals

\[ O_{5,i} = \sum_{j=1}^{i} w_j f_j = \sum_{i} w_i \]  

(5) In other to identifying appropriate input vector the following combinations that contain various values of river discharge and SSL are regarded as the input: \( 1-Q_1, 2-Q_1, 4-Q_1, 3-Q_1, \) and \( S_{1-3}, 4-Q_1, Q_{1-3}, \) and \( S_{1-3}, \) where \( Q_i \) and \( S_{i-3} \) are streamflow and suspended sediment concentration respectively. Because available data include a wide range of data, in this study by using equation (6) data were normalized in the range of .1 and .9. Then training (65%), validation (15%) and test (20%) data set were selected.

\[ y = 0.8 * \frac{X_i - X_{min}}{X_{max} - X_{min}} + .01 \]  

(6)

Where, \( Y \) and \( X_i \) represent the original variable and the standardized value respectively, while \( X_{max} \) and \( X_{min} \) are the maximum and the minimum values. RMSE and correlation coefficient (R) statistics are used as evaluation criteria.

\[ RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Q_i - Q_s)^2} \]  

(7)

Where \( Q_s \) is the simulated suspended had and \( Q_s \) is the observed suspended load.

III. RESULTS AND DISCUSSION

In the MLP, running of the model consider using of different types of inputs. The best structure of ANN determined according to the different inputs, RMSE and R, result shows in tables 1. In this table, the numbers in the parenthesis show the number of the nods in the hidden layer. As shown, input \( 3(\bar{Q}_i, Q_{1-3}) \) is the best input combination according to the RMSE and correlation coefficient. Further more, ANN with four nods in the hidden layer selected as the best structure.

In the fuzzy logic triangular, Gaussian and Bell shape membership functions for in puts and out puts used. The results of the different fuzzy logic models showed in table 2. The model with discharge as input and Gaussian membership function had the best performance. Also ANFIS model result show in table 3. For ANFIS models with triangular, Gaussian and Bell shape membership functions were tried. From table 3 can see ANFIS model with input \( Q_i \) and triangular membership functions had the best application.

The multi variant regression relation between inputs and suspended load and sediment rating curve were developed. The equation (8) shows this relation for sediment rating curve.

\[ y = 0.5903(Q_i)^{1.49} \]  

(8)

The results of different regression showed in tables 4. Considering all table show that ANFIS method seems to be better than other methods. The results of different methods for estimating of the suspended load were shown in figures 4, 5, 6 and 7.

Because of the non-linear relations between flow and sediment discharges and inefficiency of classic methods, different Artificial Intelligence methods used for modeling this non-linear relation. The results of ANFIS and FIS show that the increasing of the number of input data didn’t increase the efficiency of models and models with one input has better performance than, other models. Also the precipitation could be test as an input parameter that has an important influence on peak discharge in different Artificial Intelligence methods used for modeling of model done by Mamdani fuzzy function. Kisi (2005) obtained similar result in Quebrada Blanca station. Learning of Fuzzy logic with just one input has better accuracy than sediment rating curve and the others; but for more than one input the multi-variant regression results is better. But Kisi (2005) results of Fuzzy logic models are similar with sediment rating curve that in our results doesn’t obtained. Our results showed that ANN estimates the suspended better than fuzzy logic but Dogan et al (2005) obtained different result in Lower Sakarya River in Turkey. The cause of this difference maybe that in the fuzzy logic past experience could be used for definition of laws but there is no special pattern for determining of the membership function and that's parameter, so this parameter determined by using try and error. Further more Dogan et al (2005) used One Order Sugeno fuzzy model but in this research development of model done by Mamdani fuzzy function. Kisi (2005) obtained similar result in Quebrada Blanca and Rio Valencia stations. Generally, the artificial intelligence methods show better results than sediment rating curve and these methods are suggested for estimating of the sediment suspended load.

In this paper two methods of try and error in FIS and determining the membership's function using ANN in ANFIS used for determining of membership function's parameters. The results show that determining the membership function by ANN causes better result in fuzzy logic methods. We suggest the other methods like Genetic Algorithm and particle swarm optimization for optimizing of membership functions parameters. Also the precipitation could be test as an input parameter that has an important influence on peak discharge in all models and analysis the effect of in model accuracy. In this research using just one station consider for estimation of suspended load so we suggest that in the next research other stations could used as an input and investigate effect on those on model accuracy.
REFERENCES


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<tr>
<th>Table I</th>
<th>THE BEST STRUCTURE OF ANN BASE ON RMSE AND R</th>
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<tr>
<td>Structure</td>
<td>$Q_t$, $S_{t,1}$, $Q_{t-1}$</td>
</tr>
<tr>
<td>RMSE</td>
<td>R</td>
</tr>
<tr>
<td>ANN(2)</td>
<td>6,050 0.831</td>
</tr>
<tr>
<td>ANN(4)</td>
<td>5,884 0.818</td>
</tr>
<tr>
<td>ANN(5)</td>
<td>8,106 0.615</td>
</tr>
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<td>ANN(7)</td>
<td>7,257 0.730</td>
</tr>
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<tr>
<th>Table II</th>
<th>TRIANGULAR, GAUSSIAN AND BELL SHAPE RESULT IN FUZZY LOGIC MODELING BASE ON RMSE AND R</th>
</tr>
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<tbody>
<tr>
<td>Structure</td>
<td>$Q_t$, $S_{t,1}$, $Q_{t-1}$</td>
</tr>
<tr>
<td>RMSE</td>
<td>R</td>
</tr>
<tr>
<td>Triangular</td>
<td>10,528 0.60</td>
</tr>
<tr>
<td>Gaussian</td>
<td>10,370 0.55</td>
</tr>
<tr>
<td>Bell</td>
<td>9,968 0.67</td>
</tr>
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Table 3. RMSE and R results of ANFIS model with Bell, Gaussian and Triangular function

<table>
<thead>
<tr>
<th>Structure</th>
<th>$Q_t$, $S_{t,1}$, $Q_{t-1}$</th>
<th>$Q_t$, $S_{t,1}$</th>
<th>$Q_t$, $Q_{t-1}$</th>
<th>$Q_t$</th>
</tr>
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<tbody>
<tr>
<td>Bell</td>
<td>6.245 0.8</td>
<td>7.385 0.8</td>
<td>113.52 6</td>
<td>6.236 0.81</td>
</tr>
<tr>
<td>Gaussian</td>
<td>29.350 0.6</td>
<td>24.385 0.6</td>
<td>69.196 0.52</td>
<td>33.15 0.10</td>
</tr>
<tr>
<td>Triangular</td>
<td>8.38 0.5</td>
<td>6.022 0.8</td>
<td>56.518 0.62</td>
<td>5.441 0.88</td>
</tr>
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<tr>
<th>Table IV</th>
<th>THE RESULTS OF DIFFERENT REGRESSION RELATIONS BASE ON RMSE AND R</th>
</tr>
</thead>
<tbody>
<tr>
<td>Input</td>
<td>$Q_t$, $S_{t,1}$, $Q_{t-1}$</td>
</tr>
<tr>
<td>RMSE</td>
<td>64.09</td>
</tr>
<tr>
<td>R</td>
<td>0.78</td>
</tr>
</tbody>
</table>
Fig. 1 Brandywine basin, basin outline, stream’s gauging stations, and dams

\[ a = f(wp) \]

Fig. 2: Schematic view of neuron

\[ a = f(wp + b) \]

Fig. 3 Equivalent ANFIS architecture

Fig. 4 Comparison of observed and estimated data using ANFIS
Fig. 5 Comparison of observed and estimated data using Regression

Fig. 6 Comparison of observed and estimated data using ANN

Fig. 7 Comparison of observed and estimated data using FIS