NEW HYBRID LEARNING ALGORITHMS IN ADAPTIVE NEURO FUZZY INFERENCE SYSTEMS FOR CONTRACTION SCOUR MODELING

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ABSTRACT

An accurate prediction of maximum scour depth is necessary for a safe design of every object placed on or adjacent to a riverbed. This paper, introduces the application of some new hybrid learning rules on ANFIS technique as an alternative to the common hybrid learning methods in prediction of contraction scour depth. Differently from the common hybrid rule which combines the gradient method and the least squares estimate, new hybrid learning rules combine the Levenberg-Marquardt and the gradient methods, as well as the Levenberg-Marquardt method and the least squares estimate. To this aim, MATLAB toolbox is used to build ANFIS models based on common learning rules and FORTRAN programming language is utilized to construct ANFIS models for the proposed hybrid learning algorithms. The results of the proposed methods are evaluated and compared with similar networks trained with the common Back-Propagation and Hybrid learning algorithms which are widely used in literature for hydraulic issues.

Keywords: Adaptive Neuro Fuzzy Inference Systems, Levenberg-Marquardt method, contraction scour

1. Introduction

Scouring occurs due to several different reasons. One is the so called contraction scour which is often encountered in natural rivers due to channel contraction or river restoration structures. When the flow area is reduced by a natural contraction or bridge opening, the velocity and bed shear stress will be increased as required by continuity and momentum considerations. The higher velocity results in an increased erosive force so that more bed material is removed from the contracted reach. As a consequence of which, the bed elevation is lowered and a scour hole develops over the general bridge cross section. Contraction scour is classified as either clear-water or live-bed. In the clear-water case, no sediment transport occurs upstream of the contraction, while in live-bed case, sediment is transported from upstream through the contraction scour area. Further, two different contraction types can be specified: the short one and the long one, according to the ratio of the length of the contraction to the width of the approaching flow. Figure 1 shows the schematic of a rectangular contraction, where d_s is equilibrium scour depth [m], L is length of contraction [m], h_1 is approaching flow depth, h_2 is flow depth in contracted depth [m], b_1 is approaching channel width [m], and b_2 is contracted channel width [m]. In the literature different statements for the threshold of the ratio L/b_1 by which the contraction is designated as whether long or short can be found. For example Komura (1966) terms a contraction as long when values of $L/b_1 > 1$ are predominant, whereas Webby (1984) sees values of $L/b_1 > 2$ as relevant. Several contraction scour formulas have been developed for the evaluation of the equilibrium scour depth. Different approaches from theoretical estimation over laboratory to field data were used. Due to the complexity of scour most of them were accomplished in flumes under clear-water conditions. However, despite the many years of research into contraction scour, no formula exists, which is generally applicable to all circumstances. The reasons are assumed in the complexity of contraction scour and in limitations of the nonlinear regression, which was mainly used for contractions scour formulae derivation by earlier investigators. Recognizing these difficulties and the importance of contraction scour, it is reasonable to explore new methods for its prediction. Recently, fuzzy inference systems have been recognized as a potentially valuable tool for modeling complex non-linear systems.The main objective of this paper is to analyze the capability of ANFIS with different learning algorithms for predicting of contraction scours. To this aim, some new learning algorithms for ANFIS are written in FORTRAN language and the calculated results are compared with those using common learning algorithms.

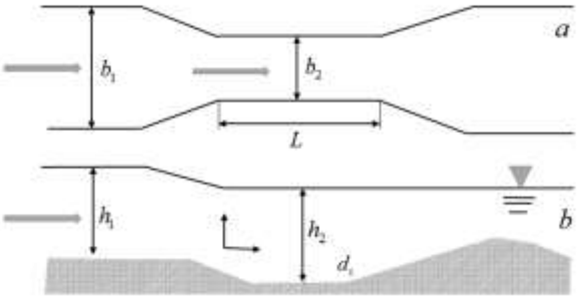

Figure 1: Schematic of a long rectangular channel contraction at equilibrium scour conditions: (a) top view; (b) side view, (Dey & Raikar, 2005)

2. ANFIS model

Adaptive network based fuzzy inference system (ANFIS) is a neuro fuzzy technique where the fusion is made between the artificial neural network (ANN) and the fuzzy inference system (FIS). Based on the differences between the specification of the consequent part and the defuzzification schemes, several types of FIS have been proposed. Among them the Takagi-Sugeno's (TS's) system (Takagi & Sugeno, 1985) is the most common one, which will be used also in this study. An ANFIS is a network structure consisting of a number of nodes connected through directional links. Each node is characterized by a node function with fixed or adjustable parameters. The learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. The basic learning rule is based on the well-known back-propagation method, which seeks to minimize some measure of error, usually the sum of squared differences between network's outputs and desired outputs. In first-order TS's system, a typical rule set with two fuzzy rules and four membership functions can be expressed as (Sayed *et al.*, 2003):

- Rule 1: If x is A_1 and y is B_1, then $f1 = p_1x + q_1y + r_1$
- Rule 2: If x is A_2 and y is B_2, then $f2 = p_2x + q_2y + r_2$

Where x and y are inputs; f_1 and f_2 are output levels. It should be noted that the possible number of rules for an ANFIS model with two inputs and two membership functions is four while in the above equation just two rules are considered for simplicity in explanation. This means that the two cases "if x is A_1 and y is B_2" and "if x is A_2 and y is B_1" are not considered. The ANFIS contains now five layers with the following processes:

- Layer 1: Each node in this layer produces membership grades of an input variable. The output of i-th node in layer l is denoted as O. Assuming a generalized bell shaped function as the membership function, the output can be computed as:

$$O_j^1 = \frac{1}{1+\left(\left(x-c_i\right)/a_i\right)^{2N_i}}; \quad i=1,2 \tag{1}$$

Where $\{a_i, c_i, N_i\}$ are adaptable variables known as premise parameters. The outputs of this layer are the membership values of the premise part.

- Layer 2: Every node in this layer multiplies the incoming signals as:

$$O_j^2 = w_j = \mu_{Aj}(x)\times\mu_{Bj}(y), \quad j=1,2 \tag{2}$$

- Layer 3: The *j*-th node of this layer calculates the normalized firing strengths as:

$$O_j^3 = \overline{w}_j = \frac{w_j}{w_1 + w_2}, \quad j = 1,2 \tag{3}$$

- Layer 4: Node *j* in this layer calculate the contribution of the *j*-th rule towards the model output, with the following node function:

$$O_j^4 = \overline{w}_j f_j = \overline{w}_j \left(p_j x + q_j y + r_j\right), \quad j = 1,2 \tag{4}$$

- Layer 5: The single node in this layer calculates the overall output of the ANFIS:

$$O_1^5 = \overline{w}_1 f_1 + \overline{w}_2 f_2 = \frac{1}{w_1 + w_2}\left[w_1\left(p_1 x + q_1 y + r_1\right) + w_2\left(p_2 x + q_2 y + r_2\right)\right] = f \tag{5}$$

More details about the ANFIS approach can be found in Jang & Sun (1997).

3. ANFIS learning rules

Learning or training phase of a neural network is a process to determine parameter values to sufficiently fit the training data. The basic learning rule are the well-known back-propagation (BP) and hybrid methods which try to minimize some measure of error, usually sum of squared differences between network's outputs and desired outputs. However, ANFIS is a network architecture that allows systematic calculations of gradient vectors (derivatives of output error with respect to modifiable parameters), so we are not limited to the back-propagation or hybrid learning method only. In fact, we can apply any gradient-based techniques in nonlinear regression and optimization, such as the Gauss-Newton method, the Levenberg-Marquardt (LM) method, the extended Kalman filter algorithm etc. The LM method is an efficient nonlinear least-squares approach to nonlinear problems, which was proposed by Jang and Mizutani (1996). Applying to ANFIS training, the LM method could reduce the root mean square error further than other methods. This paper attempts to introduce the application of two new hybrid learning rules as an alternative to common learning rules in MATLAB for predicting of contraction scour depth. Differently from the common hybrid learning rule which combines the gradient method and the least squares estimate (LSE) to identify parameters, the two new proposed hybrid rules are combination of LM and LSE methods (called New Hybrid 1), as well as of LM and BP methods (called New Hybrid 2).

4. Inputs and output for anfis model

Considering a channel with rectangular cross sections and a long contraction (that means the ratio of the length of the contraction to the width of the approaching flow is larger than 1), the physical parameters influencing the equilibrium scour depth d_s [m] in a long contraction are the approaching flow velocity v_1 [m/s], the approaching flow depth h_1 [m], the density of water ρ [kg/m^3], the density of sediment ρ_s [kg/m^3], the acceleration of gravity g [m/s^2],the kinematic viscosity of water ν [m^2/s], the median sediment particle size d_m [m], the approaching channel width b1 [m], contracted channel width b_2 [m], and geometric standard deviation of the grain-size distribution σ_g [-]. Following Dey and Raikar (2005), we can rewrite the relation between the ten physical variables of the dimensional contraction scour form into the non-dimensional functional relation with only six dimensionless variables:

$$\overline{d_s} = \frac{d_s}{b_1};\ \overline{d} = \frac{d_m}{b_1};\ \overline{h} = \frac{h_1}{b_1};\ \overline{b} = \frac{b_2}{b_1};\ \overline{Fr} = \frac{v_1}{\sqrt{\Delta g d_m}};\ \Delta g = \left(\frac{\rho_s - \rho}{\rho}\right) g \tag{6}$$

The channel opening ratio $\overline{b}$ shows the influence of geometric contraction on the degree of contraction scour. $\overline{d}$ represents the impact of sediment size on scour depth. $\overline{h}$ refers to the importance of approaching flow depth on scour depth. σ_g indicates the role of sediment gradation on scour depth and accounts also for armoring in well graded sediments. The densimetric Froude number $\overline{Fr}$ considers the effect of the mobility of submerged sediment particles on scour depth. In the ANFIS model, these five parameters are considered as model inputs. The dimensionless equilibrium scour depth is considered as the only output parameter.

5. Results and discussion

The performances of models were evaluated utilizing correlation coefficient (R), root mean square error (RMSE), and mean absolute error (MAE). The R parameter clarifies relation between observed and predicted values and RMSE evaluates the residual between observed and predicted contraction scour. Different ANFIS models were established to estimate maximum equilibrium contraction scour. Altogether 96 different ANFIS models were configured with three different types of membership functions: Gaussian, bell-shaped, trapezoidal and triangular functions for inputs as well as zero-order and first-order Sugeno's functions for output. The number of MFs for inputs ranged from two to four. After an extensive trial and error search for various networks, an optimal ANFIS model has been found for each model. The calculated results of the statistical performance indices show that for the ANFIS model trained with the common hybrid rule two bell-shaped membership functions for input with first-order Sugeno's function for output are performing best. The model with four Gaussian membership functions provides the best accuracy by training with the common back-propagation. The model combining LM and BP provides the best results by using two triangular functions with first-order Sugeno's function. The model combining LM and LSE provides the best results by using three triangular functions with zero-order Sugeno's function. Table 1 presents the statistical performances of each model for test and all data set.

Table 1: Statistical performances of the models in contraction scour depth estimation

Method	Test Data			All Data		
	R	RMSE [*m*]	MAE [*m*]	R	RMSE [*m*]	MAE [*m*]
Back-Propagation	0.9697	0.0081	0.0062	0.9746	0.0079	0.0057
Common Hybrid	0.9439	0.0108	0.0091	0.9752	0.0074	0.0054
Levenberg-Marquardt	0.9875	0.0059	0.0045	0.9791	0.0067	0.0037
New Hybrid 1	0.9834	0.0066	0.0050	0.9750	0.0072	0.0050
New Hybrid 2	0.9780	0.0068	0.0052	0.9569	0.0094	0.0068

According to Table 1, for prediction of maximum equilibrium contraction scour, the ANFIS configuration trained with the LM method as well as with the proposed hybrid rule combining of LM and BP methods provides the best efficiency for the test, and also, for the whole data set. Based on this utilized ANFIS model, all of the statistical performance indices have the lowest values comparing to those obtained from other methods. Table 2 presents exemplarily the CPU runtime required for the same number of epochs and membership function using different learning rules. It is obviously that new proposed hybrid methods need significantly less CPU runtime in comparison to LM method. Considering both the statistical indexes and the CPU runtime, we can say that the two new methods provide better model performance than the other one. Figure 3 presents a graphical comparison between different ANFIS models for the testing data. Again, it can be seen that the ANFIS model trained with combining LM and BP methods comes up with better results for contraction scour depth prediction rather than other models. The calculated results of ANFIS model using LM and BP methods are closer to 45^{o} straight line in the scatter plots compared with the others. It should be emphasized that by using the common hybrid method and the new hybrid 2 method, negative (unphysical) values of scour depth could be obtained during and after training processes.

Table 2:CPU runtime

Method	CPU Runtime [s]				
	Hybrid	**Back-Propagation**	**New Hybrid 1**	**New Hybrid 2**	**Levenberg-Marquardt**
2trimf-C	0.0608	0.0446	0.1060	0.0836	1.5725
3trimf-C	0.5945	0.8117	1.2836	0.9342	28.0601
4trimf-C	53.9704	20.0639	109.0013	96.1268	208.0040
2trimf-L	0.5865	0.0622	0.9560	0.8110	3.1486
3trimf-L	89.2813	1.0570	116.6921	101.0584	330.3758
4trimf-L	107.9401	22.4231	270.5501	210.2288	22979.6200

Note: 2trimf-C means 2 triangular membership functions with constant Sugeno's function
4trimf-L means 4 triangular membership functions with linear Sugeno's function

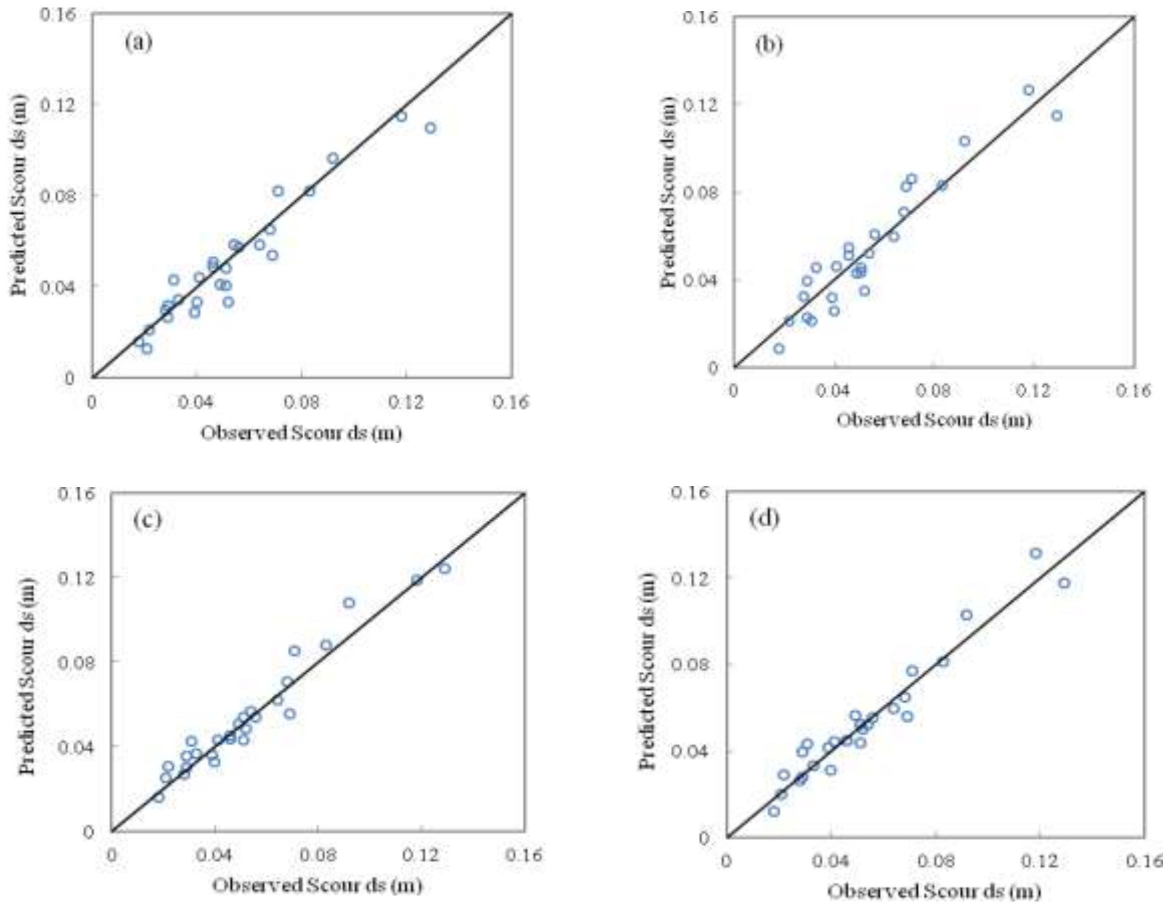

Figure 3: Correlation plots for testing data; (a) Common Back-Propagation, (b) Common Hybrid (BP + LSE), (c) New Hybrid 1 (LM + BP), (d) New Hybrid 2 (LM + LSE)

6. Conclusion

Two new hybrid learning rules which combine the Levenberg-Marquardt and the gradient method, as well as Levenberg-Marquardt and the least squares estimate were applied on an adaptive Neuro-Fuzzy inference system for predicting the equilibrium contraction scour depth. The results demonstrated that the ANFIS configuration trained with the new proposed hybrid rule combining LM and BP methods provides the best efficiency for the test and all data set. The advantage of this proposed method compared to the LM method is that it decreases significantly the CPU time, since the calculation of huge Jacobean matrix for consequent parameters was not needed. It was also showed that the results of ANFIS model trained with combination of LM and LSE is comparable with other method and can be used as an alternative to them.

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