SCOUR PREDICTION AT THE CONTROL STRUCTURES USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

An assessment of maximum scour depth with reasonable accuracy at a grade control structure is of paramount importance for its proper planning, design and management. Most of the scour depth prediction formulae available in the literature have been developed based on the analysis of the laboratory/field data using the statistical method such as the regression method (RM). Conventional statistical analysis is generally replaced in many fields of engineering by the alternative approaches such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). These recent techniques have been reported to provide better solutions in cases where the available data is incomplete or ambiguous by nature. An attempt has been made herein to develop an ANFIS model for the prediction of scour depth at the grade control structures on the bed of non-uniform sediments using the sizable amount of data and make the comparative study for the performance of ANFIS model over the RM model for the scour depth prediction at the grade control structures. It was found that the AFIS models performed better than the regression models.

INTRODUCTION

Scour is a natural phenomenon caused by the erosive action of the flowing stream on the sediment beds. Grade-control structures (Fig. 1) are generally constructed to prevent degradation in alluvial channels where the general bed slope is high. However, the local scour occurs significantly downstream of the structures due to the erosive action of the flowing water, which may undermine the foundation leading to the structure failure. An assessment of maximum scour depth with reasonable accuracy is, therefore, an essential for proper planning, design and management of such hydraulic structures.

A number of attempts have been made to model the local scour downstream of the hydraulic structures based on the various approaches in the past [1]. The laboratory investigations on local scour under various flow conditions and structure configuration have been carried out extensively in the past and results of these investigations are available in the literature. Veronese[2] analyzed the scour mechanism downstream of a spillway furnishing empirical relations to evaluate the main geometric parameters of scour depth and length. The scour induced by plane jets in different hydraulic conditions were investigated extensively by Rajaratnam[3] and Rajaratnam and Macdougall [4] . Ali and Lim [5] investigated the local scour caused by submerged wall jets. An extensive study and comparison of all the existing scour depth equations for different structures was carried out by Mason and Arumugam[6]. Bormann and Julien [1] reviewed the experimental research on scour downstream of the hydraulic structures due to free and submerged jets. They investigated the scour downstream of grade control structures with large-scale experiments using unit discharge up to 2.5 m^3 / s and scour depths exceeding 1.4 m. They also carried out a theoretical investigation based on two-dimensional jet diffusion and particle stability, proposing equations for the equilibrium scour depth. Mossa[7] carried out experimental study on the scour downstream of grade-control structures. D'Agostino and Ferro [8] deduced the physically based dimensionless parameters controlling the geometrical pattern of the scour profile at the control structures based on the self-similarity (ISS) theory and proposed the scour prediction equations on these parameters using the comprehensive laboratory scour data and the field data available in literature with different bed grain-size distributions and scales of the erosive phenomenon. Lenzi and Comiti [9] analyzed local scouring downstream of 29 drop structures, and Marion et al. [10] conducted a series of tests to determine the effect of bed sill spacing and sediment grading on the potential erosion by jets forming over the sills.

Most of the scour depth prediction formulae available in the literature have been developed based on the analysis of the laboratory/field data using the statistical method such as the regression method (RM). Conventional statistical analysis is generally replaced in many fields of engineering by the alternative approaches such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS). The ANN and ANFIS are generally preferred by various investigators due to so many relative advantages. Some of the important advantages are: the physics of the underlying phenomenon need not be known beforehand; no mathematical model needs to be assumed a priori; and the ANN is neither required to omit a large number of input variables nor use them after making simplification or specifying upper or lower bounds, contrary to conventional analytical schemes.

Guven and Gunal [11] developed an explicit neural network formulation for scour depth prediction at the control structures and the optimal neural networks were obtained using genetic algorithm. The performance of the proposed neural networks models was found to be superior to other regression –based equations. Zadeh and Kashefipour [12] modeled local scour on loose bed downstream of grade-control structures using scour data of D'Agostino and Ferro [8].The ANN models were found to be satisfactory and superior to the traditional nonlinear regression based prediction models. Goel and Pal [13] applied support vector machines for scour depth prediction at the grade-control structures and found that the support vector machines-based modeling approach gives a better performance in comparison to both the empirical relation and back propagation neural network approach with the laboratory data.

The ANN may, however, have their own limitations in directly addressing and understanding physics of the underlying process and as such they may not completely replace existing mathematical or physical modeling. The ANN is also associated with difficulties like lack of success in a given problem and unpredictable level of accuracy that could be achieved. It therefore becomes necessary that their usefulness vis-à-vis the traditional methods are checked for every application and their performance is ascertained by trying out different combinations of network architectures and learning schemes.

The problem of inherent uncertainties in the physical process and its modeling may also be easily addressed by a fuzzy logic approach. The fuzzy inference system (FIS) has been employed in the prediction of uncertain systems because its application does not require knowledge of the underlying physical process as a precondition [14-18]. A hybrid scheme using the learning capability of the ANN to derive the fuzzy if-then rules with appropriate membership functions and worked out from the training pairs leading to the inference is known as Adaptive Neuro-Fuzzy Inference System (ANFIS).

As far as scour at any structure is concerned, it is very complex phenomena; it is difficult to obtain any exact analytical models. The statistical or the soft computing is the only alternative. An attempt has, therefore, been made herein to develop ANFIS models for the prediction of scour depth at the grade control structures using the sizable amount of data and make the comparative study for the performance of ANFIS over the regression method (RM) in modeling the scour depth at the grade control structures.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The fuzzy approach is based on linguistic expressions that contain ambiguity rather than numerical probabilistic, statistical or perturbation approaches [19]. The fuzzy logic system is good at knowledge acquisition and handling such fuzzy information as an expert's experience with respect to the observed input–output data. The fuzzy logic system has been widely applied to modeling, control, identification, prediction, etc. But the fuzzy model lacks a self-learning and adaptive ability. The neural network has been shown to possess a learning and adaptive ability to input–output data. It is proved to have a good approximate capability for a wide range of nonlinear function and has been modeled for nonlinear dynamic systems. But in system modeling, network training results in a black-box representation. The model developed is difficult to interpret through human language [20].The ANFIS is a hybrid scheme which uses the learning capability of the ANN to derive the fuzzy if-then rules with appropriate membership functions worked out from the training pairs leading finally to the inference. The major difference between ANN and ANFIS is that while the former captures the underlying dependency in the form of the trained connection weights; the latter does so by establishing the fuzzy language rules.

There are two types of fuzzy inference systems: (i) Mamdani-type [21] and (ii) Takagi– Sugeno (TS)-type [22]. Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology and was among the first control systems built using fuzzy set theory. Mamdani approach provides the outcome of the fuzzy rule as a fuzzy set for the output variable and hence the step of defuzzification is essential to get a crisp value of the output variable, whereas the TS approach does not require a classical defuzzification procedure and the outcome of the fuzzy rule is a scalar rather than a fuzzy set for the output variable. The main problem associated with the TS fuzzy logic modeling is related to the selection of the parameters. An effective method is, therefore, required to tune the membership functions so as to minimize the error measures. Jang [23] proposed the ANFIS approach to optimize the parameters of the membership functions and the consequent part by using a hybrid learning algorithm. The fuzzy model parameters may be estimated by various approaches such as clustering techniques, genetic algorithms, gradient decent algorithms and numerical analysis. The neural network back-propagation learning algorithm and the least squares method are, however, simple and efficient methods and generally employed to estimate the membership function parameters and the consequent part parameters, respectively [18].The details of ANFIS Architecture has been provided in APPENDIX-I.

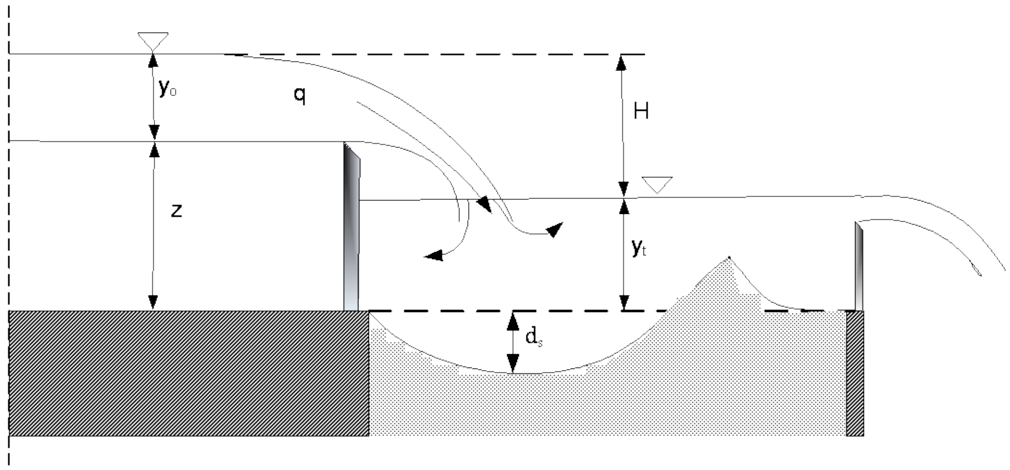


Figure 1. Definition sketch for scour downstream of the grade control structures

Şen and Altunkaynak [24] used fuzzy logic on hydrology for rainfall–runoff modeling. Fuzzy regression has been employed to investigate the modeling uncertainty in the prediction of bridge pier scour by Johnson and Ayyub [25]. Shrestha *et al.* [26] carried out the fuzzy-rule-based control systems for reservoir operation. Kindler [27] applied fuzzy logic for optimal water allocation. Bardossy and Disse [28] employed it to model the infiltration and water movement in the unsaturated zone. Pongracz *et al.* [29] reported that fuzzy-rule-based methodology on regional drought provided an excellent tool. Altunkaynak *et al.* [30-31] applied the fuzzy logic approach in the modeling of time series and reported its superiority over classical approaches. Uyumaz *et al.* [18] developed a fuzzy logic model for equilibrium scour downstream of a dam's vertical gate and indicated that a fuzzy logic model has superiority over the regression model. Bateni & Jeng [14] adopted the ANFIS-based approach for the prediction of pile group scour and found that the errors of the ANFIS model were much less than those of the conventional technique of statistical curve fitting.

SCOUR DEPTH PREDICTION MODEL

Most of the scour depth prediction formulae available in the literature have been developed based on the analysis of laboratory/field data using statistical methods such as the regression method.
D'Agostino and Ferro [8] expressed the scour depth (d_s) in dimensionless form on the basis of the incomplete self-similarity theory as

$$\frac{d_s}{z} = K\left(\frac{b}{z}\right)^{n1}\left(\frac{y_t}{H}\right)^{n2}(A_{50})^{n3}\left(\frac{d_{90}}{d_{50}}\right)^{n4}\left(\frac{b}{B}\right)^{n5} \quad (1)$$

Where b= weir width; z=fall height; y_t=tail water depth or water depth above the original bed level; H=difference in height from the upstream water level to the tail water level; A_{50} is a dimensionless parameter given as

$$A_{50} = \frac{Q}{bz\sqrt{\gamma_s g d_{50}}} \quad (2)$$

γ_s =specific gravity of the bed material; g =acceleration due to gravity; d_{50} and d_{90} =standard sieve diameter for which 50%, 90% of particles are finer respectively; Q = discharge.
It is note that H is related to z, y_0, y_t and A_{50} is a function of F_d,y_0/z and b/B ; Eq. 2 may be reduced to

$$\frac{d_s}{z} = K\left(\frac{b}{z}\right)^{n1}\left(\frac{y_t}{y_0}\right)^{n2}(F_d)^{n3}\left(\frac{d_{90}}{d_{50}}\right)^{n4}\left(\frac{b}{B}\right)^{n5} \quad (3)$$

Where F_d =Densimetric Froude number, defined as the ratio of the tractive force acting on the sediment particle to the submerged weight of the particle $=U_0/\sqrt{(\gamma_s\, gd)}$; U_0 and y_0= average velocity and flow depth at the crest.
Equation 3 is a non-linear equation wherein K is the exponent and n_1, n_2, n_3, n_4 and n_5 are the exponents of the equation. These constant and exponents are also called the parameters of the equation, which may be estimated using the non-linear least square method.

ANALYSIS, RESULTS AND DISCUSSIONS

Dataset of Scour Parameters

Laboratory data of the scour parameters relating to equilibrium scour depth at non-uniform sediment bed for the control structures in the case of clear water condition were obtained from D' Agostino and Ferro [8]. These data have been used herein for the development of the models for scour depth prediction at the control structures. The sample size of data was 202. Table 1 shows the range and statistics of the scouring parameters for theses dataset. The coefficient of variation (COV) for the relative scour depth (ds/z) is the largest where as the COV for b/B is the smallest. The COV of the dataset indicates a moderate range of data for each of the parameters except the b/B, which has held constant for most of the runs. The correlation matrix of the various scouring parameters has been provided in Table 2. This table indicates that a high inter-correlation exists between most of the variables. It also indicates that the b/z has the largest correlation with the d_s/z.

Regression Approach to Scour Depth Prediction

A nonlinear regression method was used to get the regression parameters of the scour prediction model (Eq. 3) using 80% of the available entire data selected randomly after removing outlier in the data set. It leads to the following equation for the estimation of scour depth at the grade control structures for the five different sets.

$$\frac{d_s}{z} = 0.31(F_d)^{0.79}\left(\frac{b}{z}\right)^{0.84}\left(\frac{y_t}{y_0}\right)^{-0.24}\left(\frac{d_{90}}{d_{50}}\right)^{0.91}\left(\frac{b}{B}\right)^{0.62} \quad (4)$$

The performance of this regression model evaluated in training as well as validation is provided in Table 3. It may be observed from the table that the regression model developed in the present study shows the satisfactory performance in both training and validation process.

Table 1. Range and statistics of the various scouring parameters

Parameters↓	Data range		Data statistics	
	Minimum	Maximum	Mean	COV
d_s/z	0.08	25.20	2.33	1.72
F_d	0.32	3.173	1.65	0.45
b/z	0.21	18.200	2.99	1.33
yt/y_0	0.27	7.72	2.33	0.51
d_{90}/d_{50}	1.53	5.27	2.76	0.48
b/B	0.30	1.00	0.73	0.35

Table 2 Correlation Matrix for the various scour parameters for the total data

Variables→ ↓	d_s/z	F_d	b/z	yt/y_0	d_{90}/d_{50}	b/B
d_s/z	1.000	-0.25	0.86	-0.31	0.70	0.54
F_d	-0.25	1.000	-0.48	0.075	-0.62	-0.67
b/z	0.86	-0.48	1.000	-0.35	0.73	0.66
yt/y_0	-0.32	0.075	-0.35	1.000	-0.37	-0.25
d_{90}/d_{50}	0.70	-0.620	0.73	-0.37	1.000	0.87
b/B	0.54	-0.670	0.66	-0.25	0.87	1.000

Table 3. Performance of Regression prediction models

Performance index →	r	mpe	mad	rmse
Training	0.98	-13.76	34.94	0.83
Validation	0.97	-18.88	43.88	1.012

Note: r= correlation coefficient; mpe=mean percentage error; mad=mean absolute deviation; rmse=root mean square error

Application of ANFIS to the Scour Depth Prediction

The ANFIS was employed to get the fuzzy parameters for the prediction of scour depth at the control structure in the case of non-uniform sediments. As in the previous case, here also only 80% of the available data was used for model prediction and the remaining unseen 20% of data was used for testing of the model. This was done in the MATLAB environment. ANFIS, along with a subtractive clustering method, was employed for the scour depth prediction using densimetric Froude number (F_d), relative crest width (b/z), relative tail water depth (y_t/y_0), relative sediment size (d_{90}/d_{50}) and aspect channel width ratio (b/B) as inputs and the relative scour depth (d_s/z) as output.. The optimum value of cluster radius was determined by trial and error based on the criterion of the maximum correlation coefficient and minimum root mean square error. In the present analysis we got its value to be 0.645 for which the optimum number of rules obtained was only three. The study showed that a smaller value of the cluster radius results in a large number of clusters leading to a larger number of rules, and vice versa. Larger numbers of rules take longer for calculations and it gives better prediction. However, the improvement is seen to be not a substantial one.

Figure 2 depicts the details of the initial and final membership functions (MFs), respectively. The initial and final MFs of each of the input parameters (F_d, b/z, y_t/y_o, d_{90}/d_{50} and b/B) may be compared with each other. It may be observed that there is a drastic change in the shape of Fd and b/B; a moderate change in y_t/y_o and d_{90}/d_{50}, and a slight change in b/z. The change in the shapes of MFs for an input after training reflects its influence on the output.

The details of the ANFIS parameters for the present problem have been shown in Table 5. The performance of the ANFIS was assessed qualitatively, shown in Figure 3, and quantitatively in Table 6, both for training and validation processes. Table 6 indicates that the values of mean percentage error (mpe), percentage mean absolute deviation (mad), and root mean square error (rmse) for ANFIS model are lesser than those of the regression model. It also indicates that the correlation coefficients for the ANFIS model are larger than those of the regression model. These results show that the performance of the ANFIS model is better than that of the regression models.It can be clearly observed from these that the performance for ANFIS-based modeling is satisfactory and better.

CONCLUSIONS

The scour depth prediction models downstream of the grade control stuctures on the bed of the non-uniform sediments have been developed based on the regression Method (RM) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) using moderate size of the laboratory data available in literature. The performance of these prediction models has been assessed quantitatively as well qualitatively. The ANFIS model was found to be better in performance as compared to the regression models during training as well as validation phage. It was also found that there is a drastic change in the shape of initial and final membership functions of Fd and b/B; a moderate change in y_t/y_o and d_{90}/d_{50} , and a slight change in b/z. The change in the shapes of the membership function for an input after training reflects its influence on the output.

Table 5. Details of parameters for ANFIS model

S.N.	Parameters	Number	Remarks
1	Number of nodes	44	Optimal Values of Cluster Radius=0.615
2	Number of linear parameters	18	
3	Number of nonlinear parameters	30	
4	Total number of parameters	48	
5	Number of training data pairs	159	
6	Number of checking data pairs	39	
7	Number of fuzzy rules	3	

Table 6. Performance of scour prediction models

Performance index →		r	mpe	mad	rmse
Regression Model	Training	0.98	-13.76	34.94	0.83
	Validation	0.97	-18.88	43.88	1.01
ANFIS Model	Training	**0.99**	**-4.26**	**21.40**	**0.56**
	Validation	**0.98**	**-12.46**	**28.53**	**0.85**

Note: r= correlation coefficient; mpe=mean percentage error; mad=mean absolute deviation; rmse=root mean square error

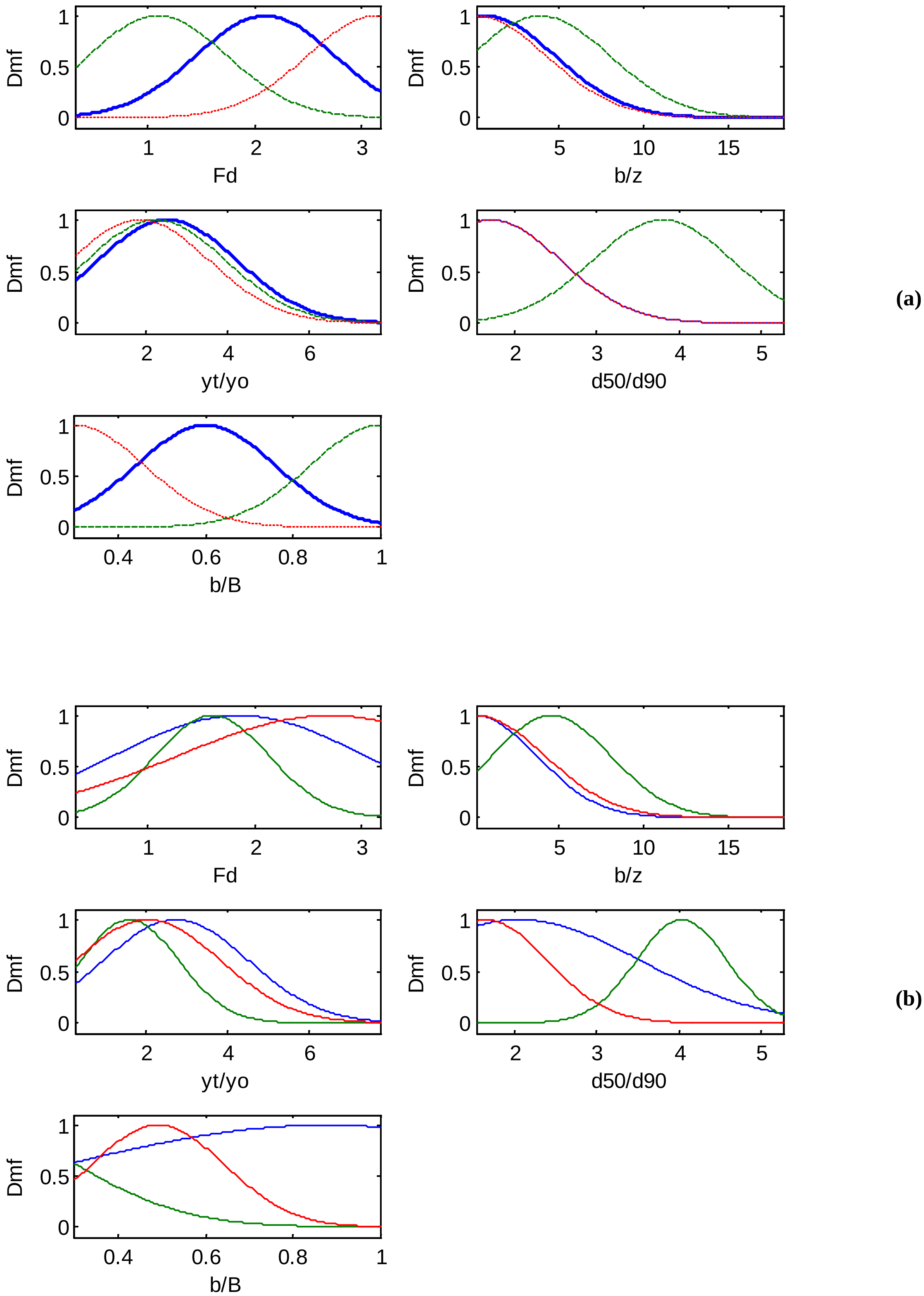
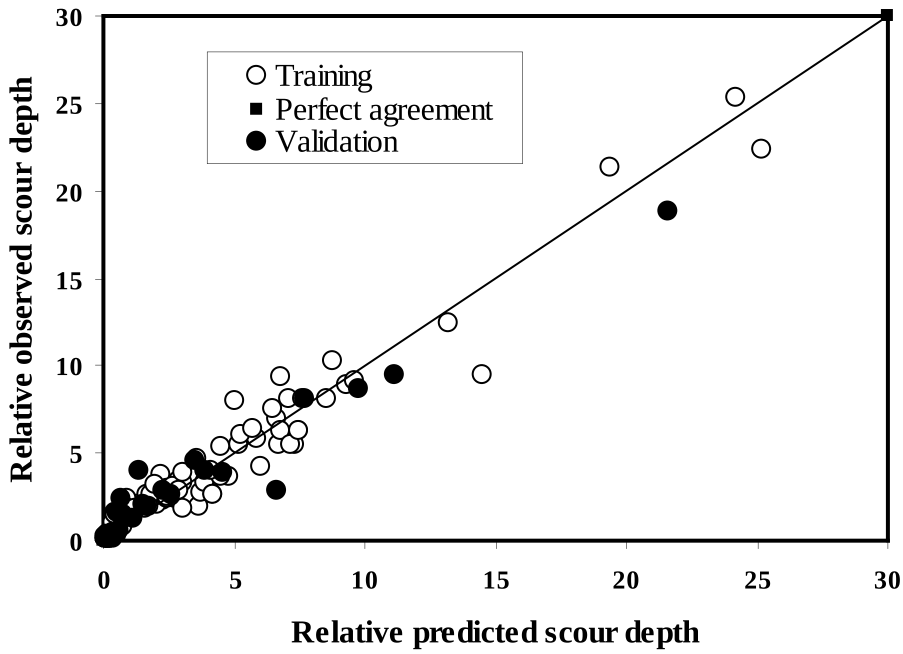
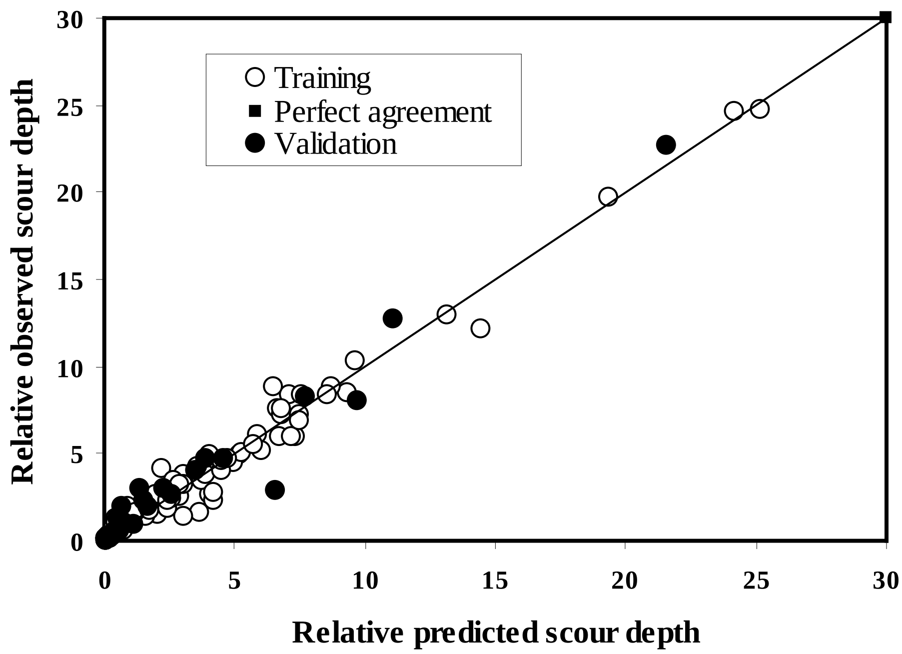


Fig. 2 Details of (a) Initial member functions and (b) Final membership functions [Dmf indicates degree of membership functions)



(a)



(b)

Fig. 3 A comparison of relative observed and predicted scour depth for (a) RM and (b) ANFIS

REFERENCES

1. Bormann, N. E., and Julien, P. Y. (1991) Scour downstream of grade control structures. *J. Hydraul. Eng.*, **117**(5), 579–594.
2. Veronese, A. (1937). Erosioni di fondo a valle di uno scarico. *Annual. Lavori Pubbl.*, **75**(9), 717–726 (in Italian).
3. Rajaratnam, N. (1981) Erosion by plane turbulent jets, *Journal of Hydraulic Research*, 19(1), 339-358.
4. Rajaratnam, N., and Macdougall, R. K.(1983). Erosion by plane wall jets with minimum tailwater. *J. Hydraul. Eng.*, **109**(7), 1061–1064.
5. Ali, K. H. M., and Lim, S. Y. (1986). Local scour caused by submerged wall jets. *Proc. Inst. Civ. Eng., Part 2. Res. Theory*, **81**, 607–645.
6. Mason, P. J., and Arumugam, K. (1985). Free jet scour below dams and flip buckets. *J. Hydraul. Eng.*, 111(2), 220–235.
7. Mossa, M. (1998). Experimental study on the scour downstream of grade-control structures. *Proc., 26th Convegno di Idraulica e Costruzioni Idrauliche*, Catanja, 581–594.
8. D'Agostino, V., and Ferro, V. (2004). Scour on alluvial bed downstream of grade-control structures. *J. Hydraul. Eng.*, **130**(1), 24–36.
9. Lenzi, M. A., and Comiti, F. (2003). Local scouring and morphological adjustments in steep channels with check-dam sequences. *Geomorphology*, 55, 97–109.
10. Marion, A., Lenzi, M. A., and Comiti, F. (2004). Effect of sediment size grading and sill spacing on scouring at grade-control structures *Earth Surf. Processes Landforms*, 29(8), 983–993.
11. Guven, A. and Gunal, M. (2008) Prediction of scour downstream of grade-control structures using neural networks, *Journal of Hydraulic Engineering* **134**(11), 1656-1660.
12. Zadeh, A.A.T. and Kashefipour, S.M. (2008) Modeling Local scour on loose bed downstream of grade-control structures using artificial neural network, *Journal of applied science*, **8**(11), 2067-2074.
13. Goel, A. and Pal , M. (2009) Application of support vector machines in scour prediction on grade-control structures, *Engineering Appilications of Artificial Intelligence* **22**, 216-223.
14. Bateni, S.M. Jeng, D.S and Melville, B. W. (2007) Basian neural networks for prediction of equilibrium and time-dependent scour depth around bridge piers, *Advances in Engineering Software, Elsevier* **38**, 102-111.
15. Bateni, S.M., Borghei, S.M..and Jeng, D.S (2007) Neural network and neuro-fuzzy assessment for scour depth around bridge piers, *Engineering Applications of Artificial Intelligence, Elsevier*, **20**, 401-414.
16. Muzzammil, M. and Alam, J. (2010). **"**ANFIS - based approach to scour Prediction at abutments in armored beds," IWA Publishing, *Journal of Hydro informatics*,699-713.
17. Muzzammil, M. and Alam, J. (2010). **"**ANFIS approach to scour depth prediction at a bridge abutment," IWA Publishing, *Journal of Hydro informatics*, 447-485.
18. Muzzammil, M. and Ayyub, M. (2010). **"**ANFIS approach to scour depth prediction at piers in non-uniform sediments," IWA Publishing, *Journal of Hydro informatics*, 303-317.
19. Uyumaz,A., AltunKaynak, A. and Ozger,M. (2006), Fuzzy Logic Model for equilibrium scour downstream of a dam's vertical gates, *Journal of Hydraulic Engineering*, ASCE, **132**(10), pp 1069-1075.
20. Sun, Q. & Cheng, M. 2005 Modeling of doubly salient permanent magnet motor based on ANFIS. In: *Proc. Eighth International Conference on Electrical Machines and Systems, ICEMS 2005*, **1**, pp 321–325.
21. Mamdani, E.H. 1974 Application of fuzzy algorithms for simple dynamic plant. *Proc. IEEE* **121**, 1585–1588
22. Takagi, T. & Sugeno, M. 1985 Fuzzy identification of systems and its application to modeling and control. *IEEE Trans. Syst. Man Cybern.* **15**, 116–132.
23. Jang, J.S.R. 1993 ANFIS: adaptive network based fuzzy inference system. *IEEE Trans. Syst. Man Cybern.* **23** (3), 665–684.
24. Şen, Z. & Altunkaynak, A. 2004 Fuzzy awakening in rainfall-runoff modeling. *Nordic Hydrol.* **35** (1), 31–43
25. Johnson, P. A., and Ayyub, B. M. (1996), Modeling uncertainty in prediction of pier scour, Journal of Hydraulic Engineering **122**(2), 66–72.

26. Shrestha, B.P., Duckstein, L. & Stakhiv, E.Z. 1996 Fuzzy rule based modeling of reservoir operation. *J. Wat. Res. Plann. Mngmnt.* **122** (4), 262–269.
27. Kindler, J. (1992) Rationalizing water requirements with aid of fuzzy allocation model, *J. Water Resour. Plan. Manage.* **118**(3) 308–323.
28. Bardossy, A. & Disse, M. 1993 Fuzzy rule based models for infiltration. *Wat. Res. Res.* **29** (2), 373–382.
29. Pongracz, R., Bogardi, I. & Duckstein, L. 1999 Application of fuzzy rule-based modeling technique to regional drought. *J. Hydrol.* **224** (3–4), 100–114.
30. Altunkaynak, A. Özger, M. & Çakmakcl, M. 2004a Water consumption prediction of Istanbul city by using fuzzy logic approach. *Wat. Res.. Mngmnt.* **19** (5), 641–654.
31. Altunkaynak, A., Özger, M. & Çakmakcl, M. 2004b Fuzzy logic modeling of the dissolved oxygen fluctuations in golden horn. *Ecol. Modell.* **189** (3–4), 436–446.

APPENDIX-I

Architecture of the ANFIS

ANFIS was firstly put forward by Jang (1993) and is classified into three types according to the types of fuzzy reasoning and fuzzy if-then rule employed. The third of them is Takagi-Sugeno ANFIS. The selection of the fuzzy inference system (FIS) is the major concern in the design of ANFIS. The present study is based on Takagi and Sugeno's fuzzy if-then rules representation, wherein the consequent part of the rule is a linear function of input variables and the parameters may be estimated by a simple least squares error method.

Fig. A1 depicts a typical architecture of ANFIS for a system with two inputs (x and y) and single output (z). The inference mechanism of ANFIS is mathematically expressed by the set of rules. These rules are generated through the experience of the system operator, design engineer, or the expert.

The k^{th} rule is generally expressed in the form (If *premise* THEN *consequence*) and is given by:

$$\text{If } (x \text{ is } A_i^k) \text{ and } (y \text{ is } B_j^k) \text{ Then } (z \text{ is } f_k = p_k\, x + q_k\, y + r_k) \tag{A1}$$

Where, A_i^k and B_j^k are the i^{th} and j^{th} fuzzy term sets of representing x and y respectively. The consequent function $f_k = p_k x + q_k y + r_k$ has parameters p_k, q_k, and r_k, which are adjustable and are tuned in training phase. Bell-shaped or Gaussian membership function is commonly considered for each fuzzy subset that is having three/two parameters. We have considered Gaussian membership function in the present study which has only two parameters,. Each fuzzy subset (say A_i) is defined by a membership function $\mu_{A_i}(x)$ as in (A2).

$$\mu_{A_i} = \exp\left(-0.5 * \left(\frac{x - c_i}{a_i}\right)^2\right) \tag{A2}$$

where a_i and c_i are the parameters of antecedent fuzzy set A_i of the i^{th} membership function. These parameters control the shape of the Gaussian membership function.

The architecture of the ANFIS in Fig. 1 has five layers. The functional details of these layers are as under:

Layer 1: This layer calculates the degree to which the given input x (or y) satisfies the term set A_i (or B_j for input y). The membership function for each term set A_i (or B_j) may be generalized bell function or Gaussian function, as described above.

The parameters (a_i, c_i) for Gaussian function respectively, are termed as premise parameters.

Layer 2: The nodes in this layer are fixed nodes labelled π. The output of each node is the product of the incoming signals. Thus the output of k^{th} node of the layer is given by:

$$w_k = \mu_{Ai}(x) * \mu_{Bi}(y) \tag{A3}$$

The output of each node represents the strength of the corresponding rule.

Layer 3: The nodes of this layer are fixed node labelled N. The i^{th} node of the layer calculates the normalized firing strength of the corresponding rule. The normalized firing strength ($\overline{w}_k$) of a rule (k^{th}) is the ratio of the strength of that rule (w_k) and sum of the strengths of all rules i.e.

$$\overline{w}_k = \frac{w_k}{\sum_k w_k} \tag{A4}$$

Layer 4: The nodes of this layer are adaptive nodes. The node function of i^{th} node of the layer is given by:

$$z_k = \overline{w}_k * f_k = \overline{w}_k * (p_k x + q_k y + r_k) \tag{A5}$$

Here $\overline{w}_k$ is the normalized firing strength of the k^{th} rule, which is obtained in layer 3, and (p_k, q_k, r_k) is the set of parameters of this layer. These parameters are referred as consequent parameters.

Layer 5: It has one node for single output, which is a fixed node labelled ∑. This node calculates the sum of all incoming signals. Thus the overall output (z) of the ANFIS is:

$$z = \sum_k z_k = \sum_k \left(\overline{w}_k * f_k\right) = \frac{\sum_k w_k * f_k}{\sum_k w_k} \tag{A6}$$

The ANFIS modelling involves two major phases: (i) structure identification and (ii) parameter estimation. The structure identification amounts to determine the proper number of rules required i.e. finding how many rules are necessary and sufficient to properly model the available data and the number of membership functions for input and output variables.

Clustering techniques have been recognized as a powerful tool to extract initial fuzzy rules from given input-output data. The purpose of the clustering is to identify natural grouping of data from a large data set to produce a concise representation of the system behaviour. Subtractive clustering is commonly used for the initialisation of the parameters for ANFIS training.

Steepest descent (or back propagation) method is applied for identification of the parameters. But this usually takes long time before it converges. In the present case we find that some of the parameters are linearly related to the output (consequent parameters). Thus these linear parameters can be identified by least square error (LSE) method, for fixed values of non-linear parameters (premise parameters). After identifying the consequent parameters (which are linear) we can apply steepest descent method for identification of premise parameters (which are non-linear parameters). This hybrid learning approach, which combines the steepest descent method and LSE method, gives fast identification of parameters. The hybrid-learning algorithm has two passes, the forward pass and the backward pass. In the forward pass the node output is calculated till layer 4. Then LSE is applied to identify the consequent parameters. After this the backward pass is done. In this, the error signal is the input and is propagated backward. From the error signal the premise parameters are calculated by applying steepest descent method. The procedure of the hybrid learning is summarized in Table 1.

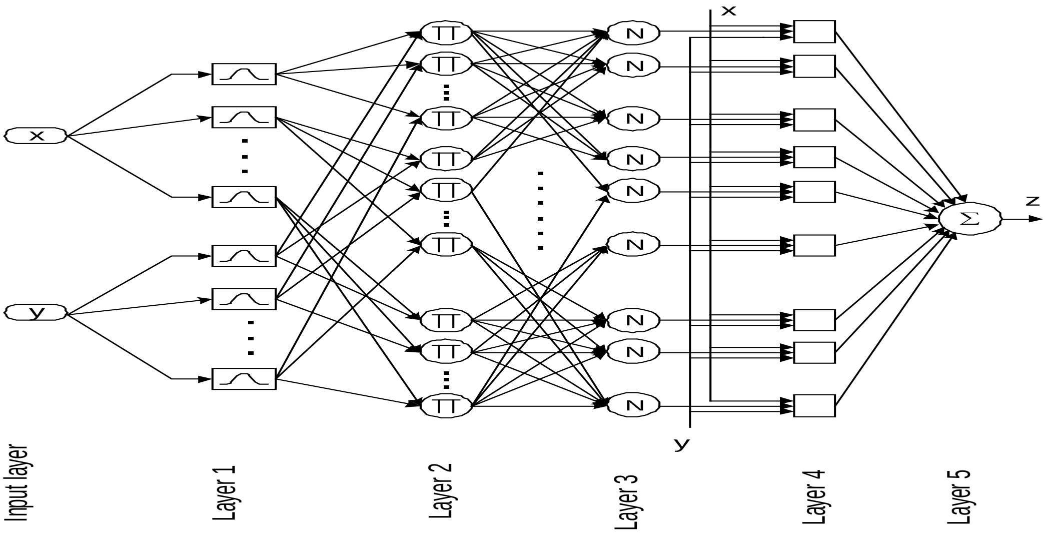


Fig. A1. Structure of a two inputs and single output ANFIS

Table1 Basic steps of ANFIS hybrid learning

	Forward pass	Backward pass
Premise parameters	Fixed	Gradient descent
Consequent parameters	LS-estimator	Fixed
Signal	Node output	Error signal

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