ANFIS approach to the scour depth prediction at a bridge abutment

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ABSTRACT

An accurate estimation of the maximum possible scour depth at bridge abutments is of paramount importance in decision-making for the safe abutment foundation depth and also for the degree of scour counter-measure to be implemented against excessive scouring. Despite analysis of innumerable prototype and hydraulic model studies in the past, the scour depth prediction at the bridge abutments has remained inconclusive. This paper presents an alternative to the conventional regression model (RM) in the form of an adaptive network-based fuzzy inference system (ANFIS) modelling. The performance of ANFIS over RM and artificial neural networks (ANNs) is assessed here. It was found that the ANFIS model performed best among of these methods. The causative variables in raw form result in a more accurate prediction of the scour depth than that of their grouped form.

Key words | ANFIS and regression analysis, bridge abutments, local scour, neural network

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NOTATION

L	width of abutment normal to the approaching flow
d_{se}	depth of scour
F	Froude number
U	mean velocity of approach flow
U_c	mean velocity of approach flow at the incipient motion of sediment
g	acceleration due to gravity
h	depth of the approaching flow
K	coefficient of regression equation
n_1, n_2, n_3	exponents of regression equation
r	correlation coefficient
β	mean absolute percentage error
γ	root mean square error
x, y	inputs to the ANFIS
z	output of the ANFIS
A_i^k	fuzzy set for input variable x
B_i^k	fuzzy set for input variable y
p_k, q_k, r_k	parameters of consequent part
f_k	consequent function
a_i, c_i	parameters of premise
$\mu_{A_i}(x)$	membership value of x in A_i
w_k	weight of kth inference rule
$\bar{w}_k$	firing strength of kth inference rule
k	rule number
R_k	kth rule
z_k	output of kth inference rule

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INTRODUCTION

When obstructions such as a bridge abutment, spur dike, pier, etc. are placed over a bed in a river stream, it leads to a three-dimensional modification of the flow due to the development of a vortex flow in the vicinity of the obstruction. In the case of abutment, the flow separates at the upstream face of the abutment as it travels by its side, creating a vortex trail that moves downstream and leads to scouring of the sediment bed in the vicinity of the abutment locally. This local scour exposes the abutment foundation that leads to the failure of the bridge. Failure of bridges due to scour at their foundations consisting of abutments and piers is a common occurrence. Local scour at foundations has long been a concern for engineers (Cardoso & Betts 1999). In the safety evaluation of bridges, local scour of bridge foundation material near pier/abutment is therefore an important issue (Huber 1991; Dey & Barbhuya 2004*a*).

Various approaches to the scour depth prediction at abutments are generally classified into three categories: (1) regime approach relating the scour depth to the increased discharge intensity; (2) empirical approach using dimensional analysis of the main parameters causing scour; and (3) analytical or semi-empirical approach. Experimental and theoretical investigations have been reported which provide a better understanding of the problem; however, it remains unexplored in many cases. From the available literature, it is also revealed that the exact scour mechanism and effects of different parameters on scour depth are yet to be fully understood or explored (Barbhuya & Dey 2004).

Bateman *et al.* (2005) developed a morphodynamic model to predict temporal evolution of local scour at bridge piers. They distinguished three different phases of the scouring process including the active, passive and equilibrium phase. The active phase is controlled by the vortex dynamics; the passive phase is due to the crumbling of sediment into the active pit. The equilibrium phase depends on the non-hydrostatic pressure distribution. The scour process was analyzed based on the concept of vortex energy dissipation and hydrological concept to recreate continuous crumbling of the scoured wall. A nonlinear system of two total differential equations was obtained, which agree very well with experimental data. However, they suggested that a deeper study of the parameters involved has to be carried out to know more about their sensitivity in the process of scour evaluation.

There is therefore no single analytically derived equation which is valid for a wide range of flow conditions, bed material properties and abutment shape configurations, because of the difficulties of precise modelling of the phenomenon in a laboratory medium. Lack of understanding of complex flow conditions and simplified modelling of the phenomenon would lead to the pronounced modelling uncertainty. On the other hand, reliable field data are scarce leading to calibration problems. Engineering solutions concerning the estimation of safe foundation depth and selection of scour protection measures would be subject to uncertainty (Yanmaz & Kose 2007).

A great deal of research effort has been devoted to exploring and refining the methods for improving traditional physical-based analysis in such situations. Recently artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) have been commonly employed as the alternative approaches to the traditional regression analysis (Bateni & Jeng 2007; Bateni *et al.* 2007*b*).

The ANNs have been widely applied to solve problems in various fields of hydrology, water resources (ASCE Task Committee 2000*a*) and sediment transport. Trent *et al.* (1993) applied neural networks to estimate scour depth at bridge piers. Kambeker & Deo (2003) applied neural networks to the scour prediction around pile groups. Azmathullah *et al.* (2005, 2006) developed the neural networks for estimation of scour downstream of a ski-jump bucket. Liriano & Day (2001) employed neural networks for the prediction of scour depth at culvert outlets. Jeng *et al.* (2005) performed the neural network assessment of scour depth around bridge piers. They indicate that the use of an ANN results in a higher level of accuracy in solving a particular problem when compared to experimental and theoretical results (providing a reliable database is available). Choi & Cheong (2006) described a method for predicting local scour around bridge piers using an ANN with emphasis on selecting input variables, calibrations of network control parameters, learning process and verifications. Wu & Lim (1993) carried out the study of prediction of maximum scour depth at spur dikes using adaptive neural networks.

The fuzzy inference system (FIS) has also been applied in numerous water resources problems. Şen & Altunkaynak (2004) used fuzzy logic on hydrology for rainfall–runoff modelling. Fuzzy regression has been employed to investigate the modelling uncertainty in the prediction of bridge pier scour by Johnson & Ayyub (1996). Shrestha *et al.* (1996) carried out the fuzzy rule-based control systems for reservoir operation. Kindler (1992) applied fuzzy logic for optimal water allocation. Bardossy & Disse (1993) employed fuzzy logic to model the infiltration and water movement in the unsaturated zone. Pongracz *et al.* (1999) reported that fuzzy rule-based methodology on regional drought prediction provided an excellent tool. Altunkaynak *et al.* (2004*a*,*b*) applied the fuzzy logic approach in the modelling of time series and reported its superiority over classical approaches. Uyumaz *et al.* (2006) developed a fuzzy logic model for equilibrium scour downstream of a dam's vertical gate and indicated that the fuzzy logic model has superiority over the regression model. Bateni & Jeng (2007) 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. Azmathulla *et al.* (2008) applied the ANNs as well as ANFIS for the estimation of the scour below spillways. They reported that the treatment to non-linearity in scour data based on the ANFIS approach worked much better than the other schemes of ANNs; the scour data could therefore be considered to be more amenable to fuzzy if-then rules than crisp value processing. Zounemat-Kermani *et al.* (2009) studied the estimation of current-induced scour depth around pile groups using ANNs and ANFIS. They found that FFBP-NN (feed forward back propagation neural networks) model provides a better prediction than the other methods under consideration.

A detailed review shows that the available literature on the application of ANN and ANFIS to the scour at abutments is limited. Further, it has also been reported that the ANNs are associated with the difficulties such as success in a given problem and unpredictable level of accuracy that could be achieved. The usefulness of ANNs and ANFIS compared to the traditional methods must therefore be checked for every application and their performance should also be ascertained by trying out different combination of network architectures and learning schemes (Azmathulla *et al.* 2008). Keeping these scopes in view, the main objective of the present study is to develop an ANFIS model (based on fuzzy logic) for scour depth prediction at the bridge abutments. The performance assessment of the ANFIS model is then compared with that of a regression model and ANN model.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

Fuzzy logic, derived from fuzzy set theory, enables approximate reasoning instead of classical predicate logic. The fundamental logical IF-THEN-ELSE construct allows for decisions that are based on the truthfulness of a logical statement. The logical statement is either TRUE or FALSE, resulting in different decisions. Fuzzy logic extends this concept by allowing a degree of truthfulness i.e. a statement can be partly true and partly false. Fuzzy set theory provides the mechanism to resolve the final decision. The main advantage of such a fuzzy logic approach is that fuzzy logic rules can be developed that exploit human knowledge. Human knowledge often relies on weighing conflicting facts (statement) of varying degrees of truthfulness. Fuzzy logic provides the framework to replicate such a decision making process (He & Valeo 2009).

Fuzzy logic systems are good at knowledge acquisition and handle such fuzzy information as expert experience with respect to the observed input-output data. The fuzzy logic system has been widely applied to modelling, control, identification and prediction, etc. (Sun & Cheng 2005; Tiwari & Ayyub 2006). However, a fuzzy model lacks in self-learning and adaptive ability. The neural network has been shown to possess learning and adaptive ability to input-output data. It has been proved to have good approximate capability for a wide range of non-linear functions and has been modelled for non-linear dynamic system. In system modelling, network training results in a black box representation. The model developed is difficult to interpret through human language (Sun & Cheng 2005).

The ANFIS is basically an integration of the techniques of fuzzy systems and ANNs. The ANN provide connectionist structures and learning abilities to the fuzzy systems whereas the fuzzy systems offer ANNs a framework for high level IF-THEN rule thinking and reasoning.

There are two types of fuzzy inference systems: (1) Mamdani and (2) Takagi-Sugeno (TS). Mamdani's fuzzy inference method is the most commonly seen fuzzy methodology and was among the first control systems built using fuzzy set theory. The Mamdani approach provides the outcome of the fuzzy rule as a fuzzy set for the output variable and hence the defuzzification step is essential to obtain a crisp value of the output variable. The TS approach, however, 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 modelling is related to the selection of the parameters. An effective method is therefore required to tune the membership functions in order to minimize the error measures. Jang proposed the ANFIS approach to optimize the parameters of the membership functions and the consequent part by using a hybrid-learning algorithm (Jang 1993). The fuzzy model parameters may be estimated by the 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 are, however, the most simple and efficient methods. They are generally employed to estimate the membership function parameters and the consequent part parameters, respectively (Uyumaz *et al.* 2006).

CONVENTIONAL SCOUR DEPTH PREDICTION

The governing parameters affecting the equilibrium clear water scour depth (d_{se}) at an abutment perpendicular to the shoreline placed in uniform bed sediments are generally expressed in the following functional form, assuming constant relative density of sediment and absence of viscous effects (Dey & Barbhuya 2004*a*,*b*):

$$d_{se} = f(U, L, h, U_c, d, K_s) \tag{1}$$

where L is the length of abutment perpendicular to the flow direction; h is the depth of approach flow; U is the mean flow velocity; U_c is the critical velocity of bed sediment and d is the median size of the sediment. K_s represents the abutment shape factor, being 1 for vertical-wall abutments, 0.82 for 45° wing-wall abutments and 0.75 for semicircular abutments.

Since the scour depth at an abutment occurs when the excess approaching flow velocity (U_e) is greater than zero, where $U_e = U - 0.5U_c$, Equation (1) may therefore be expressed:

$$d_{se} = f(U_e, L, h, d, K_s) \tag{2}$$

Equation (2) may also be reduced in terms of a set of non-dimensional parameters in the form:

$$\frac{d_{se}}{L} = f\left(F_e, \frac{h}{L}, \frac{d}{L}, K_s\right) \tag{3}$$

where $F_e = U_e/(\Delta g L)^{0.5}$; $\Delta = s - 1$; and s is the relative density of sediment particles.

The non-dimensional parametric representation in the present model has been justified by Dey & Barbhuya (2004*a*) for the following reasons.

- The term F_e is a measure of the ratio of excess approaching flow velocity U_e to $(\Delta g L)^{0.5}$. It represents the mobility of the submerged sediment particles in the vicinity of abutment during scouring. U_e is less than or equal to zero when there is no scour.
- The term h/L refers to the effect of approaching flow depth h on the scour depth d_{se}.
- The term d/L indicates the role of particle sizes of bed sediment on scour depth d_{se}.

A power law form of Equation (3) may expressed:

$$\frac{d_s}{L} = K_s K (F_e)^{n_1} \left(\frac{h}{L}\right)^{n_2} \left(\frac{d}{L}\right)^{n_3} \tag{4}$$

where K is the coefficient and n_1, n_2 and n_3 are the exponents of the equation, which may be easily obtained from the regression analysis of the observed data of scour.

ANALYSIS, RESULTS AND DISCUSSIONS

Dataset of scour parameters

Laboratory data of the scour parameters relating to equilibrium scour depth around vertical-wall, 45° wing-wall and semicircular abutments (Figure 1) for the case of clear water condition in uniform sediments were obtained from the literature (Dey & Barbhuya 2004*a*).

The time for running the experiment is generally considered to be an important variable of interest to avoid erroneous equilibrium scour depth. Lim (1997) reported that the required time to reach the equilibrium scour at abutments in clear water scour is 3–8 days, depending on the flow and sediment conditions. Melville & Chiew (1999) defined the time to reach equilibrium conditions such that the rate of increase of scour depth does not exceed 5% of the pier diameter in the succeeding 24-hour period. Dey & Barbhuya (2004*a*) reported that when a negligible (1 mm or less) difference of scour depth of a particular run was observed at an interval of 2 hours after 48 hours, it was assumed that an equilibrium state has been achieved.

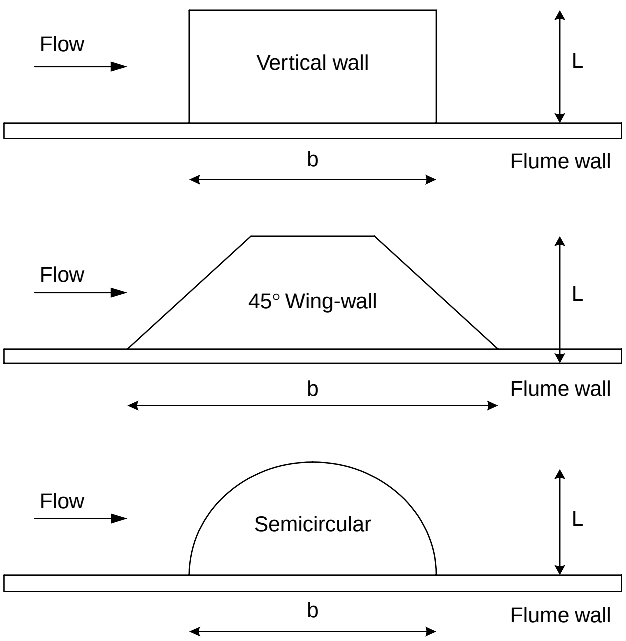

Figure 1 | Different types of abutments.

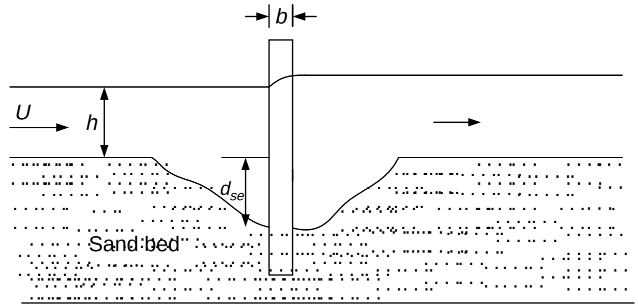

Figure 2 | Definition sketch of scour at a typical abutment.

The data of Dey & Barbhuya (2004*a*) have been used in the present study for the development of the various models for scour depth prediction at bridge abutments. The 99 data points are available for each type of abutment with different approaching depths and sediment sizes, approximately maintaining the condition $U/U_c = 0.95$. The overall sample size of the data is 297. Table 1 shows the range of parameters for this dataset. Figure 2 shows the definition sketch of scour at a typical abutment.

Regression method for the scour depth prediction using a non-dimensional dataset

A non-linear regression method was used to obtain the regression parameters of the scour prediction model (Equation (4)) using 80% of the available entire data selected randomly after removing 20% of the available data. It leads to the following equations for the estimation of scour depth at the bridge abutments:

$$\frac{d_s}{L} = 9.694\ K_s(F_e)^{0.648}\left(\frac{h}{L}\right)^{0.04}\left(\frac{d}{L}\right)^{-0.075} \quad (5)$$

$$\frac{d_s}{L} = 9.694\ K_s(F)^{0.64}\left(\frac{h}{L}\right)^{0.056}\left(\frac{d}{L}\right)^{0.082}\left(\frac{U}{U_c}\right)^{1.53} \quad (6)$$

where K_s is the abutment shape factor and is equal to 1 for vertical-wall abutments, 0.82 for 45° wing-wall abutments and 0.75 for semicircular abutments.

The present scour model (Equation (5)) is different from the pier scour model of Bateni *et al.* (2007*a*) wherein abutment Froude number ($F = U/(gL)^{0.5}$) and the flow intensity (U/U_c) were considered separately. Simarro *et al.* (2007) proved that the flow intensity is not an adequate parameter to describe the process in usual laboratory conditions. The present model also incorporates the effect of the abutment shape (K_s). Equation (6) describes the Bateni-type scour model.

Table 1 | Range for data of scours parameters used for estimation of equilibrium scour depth

Item	Parameters	Range
1	Abutment length L (m)	0.04–0.12
2	Flow depth y (m)	0.058–0.25
3	Mean velocity U (m/s)	0.219–0.67
4	Sediment size d (mm)	0.26–3.10
5	Scour depth d_{se} (m)	0.053–0.29

Table 2 | Comparison of model performance

Stages	*R*	mape	rmse
Present scour model (Equation (5))			
Calibration	0.97	7.70	0.157
Validation	0.97	6.45	0.142
Bateni-type scour model (Equation (6))			
Calibration	0.94	12.11	0.23
Validation	0.92	11.71	0..23

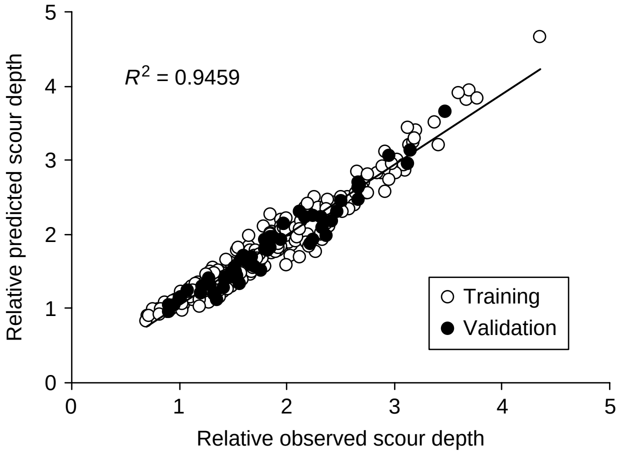

Figure 3 | Scatter diagrams of relative observed and predicted scour depths for Regression Method.

Validation of these equations was made with the help of the remaining unseen 20% of the data, which were not involved in their derivation. A quantitative comparison between observed and predicted values of scour was made in terms of three performance indices, namely (1) correlation coefficient (R), (2) the mean absolute percentage error (mape) and (3) the root mean square error (rmse). The performance indices of the regression model during calibration and validation dataset are provided in Table 2. Figure 3 indicates a qualitative assessment of RM. It may be observed that the performance of the present scour model is better than the Bateni-type scour model in both calibration as well as validation.

The scour depth prediction Equation (5) has been obtained using a regression method (RM). The following drawbacks in any RM application have been pointed out (Sun & Cheng 2005; Uyumaz *et al.* 2006).

1. The deviations of scatter points from the fitted curve have zero value with assumed constant variance. However, in the actual scatter diagram the variance is often not constant but varying depending on the independent variable value.
2. The regression curve may pass close to a certain percentage of points in the scattered diagram, but this cannot account for the validity of the method.
3. The prediction errors are expected to abide with a Gaussian distribution function, which is not the case in many practical studies.
4. The prediction errors are also expected to be independent from each other i.e. completely random (noise).

In order to avoid such problems in the application of the regression method, an alternative approach is generally advocated (Johnson & Ayyub 1996; Uyumaz *et al.* 2006).

ANN approach for scour depth prediction using non-dimensional data set

The concepts involved in ANNs along with their applications in water resources engineering are well described in the ASCE Task Force (2000*a*,*b*). Applications of ANN in the hydraulic engineering have been presented by Muzzammil & Siddiqui (2003), Azmathullah *et al.* (2005, 2006) and Bateni *et al.* (2007*a*).

With commonly used algorithms such as the Feed Forward Back Propagation (FFBP), Feed Forward Cascade Correlation (FFCC) and Radial Basis Function (RBF), the ANNs were developed in the MATLAB environment for the scour depth prediction modelling in the present study. The Levenberg-Marquardt algorithm was used for faster training. This method involves a significant training parameter μ. When μ is zero, the method simply corresponds to Newton's method. When μ is large, this becomes a gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so

Table 3 | Performance assessment of ANN models compared to regression model

Prediction models		Training *R*	Training mape	Training rmse	Validation *R*	Validation mape	Validation rmse
Regression	RM	0.973	7.70	0.1569	0.973	6.45	0.1422
	FFBP	0.99	3.29	0.075	0.99	3.23	0.079
ANN	FFCC	0.99	3.58	0.079	0.99	3.91	0.093
	RBF	0.99	4.19	0.095	0.99	4.18	0.108

the aim is to shift towards Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function will always be reduced at each iteration of the algorithm. The optimum value of μ in the present case has been found empirically to be 0.001. The method involves the training of ANN with excess Froude number (F_e), relative flow depth (h/L), relative sediment size (d/L) and shape factor (K_s) as inputs and the relative scour depth (d_{se}/L) as output. The training data was the same randomly selected 80% of the available entire data for the network that was used in the regression analysis. The remaining 20% data was used for validation. The performance of various ANN models against the regression models was assessed quantitatively in terms of performance indices, as shown in Table 3. Figure 4 indicates a relative comparision of various ANN prediction models qualitatively.

It may be observed that all the ANN models are superior to the regression models. Further, the FFBP training algorithm appears to be the best of the other training algorithms of ANN under consideration. The FFBP model may therefore be recommended for the abutment scour depth prediction.

The weights and biases of the optimal architecture of the FFBP are provided in Table 4. Figure 5 shows the network configuration that may be used for the prediction of the maximum equilibrium scour depth around bridge abutments, along with the weights and biases.

ANFIS-based models for scour depth prediction using non-dimensional parameters

The ANFIS was used to obtain the fuzzy parameters for the prediction of scour depth at the bridge abutments. As in the previous case, only 80% of the available data was used for model prediction and remaining unseen 20% data was used for the testing of the model. This was carried out using MATLAB. ANFIS and a subtractive clustering method were used for the scour depth prediction with excess Froude number (F_e), relative flow depth (h/L), relative sediment size (d/L) and shape factor (K_s) as inputs and the relative scour depth (d_{se}/L) as output.

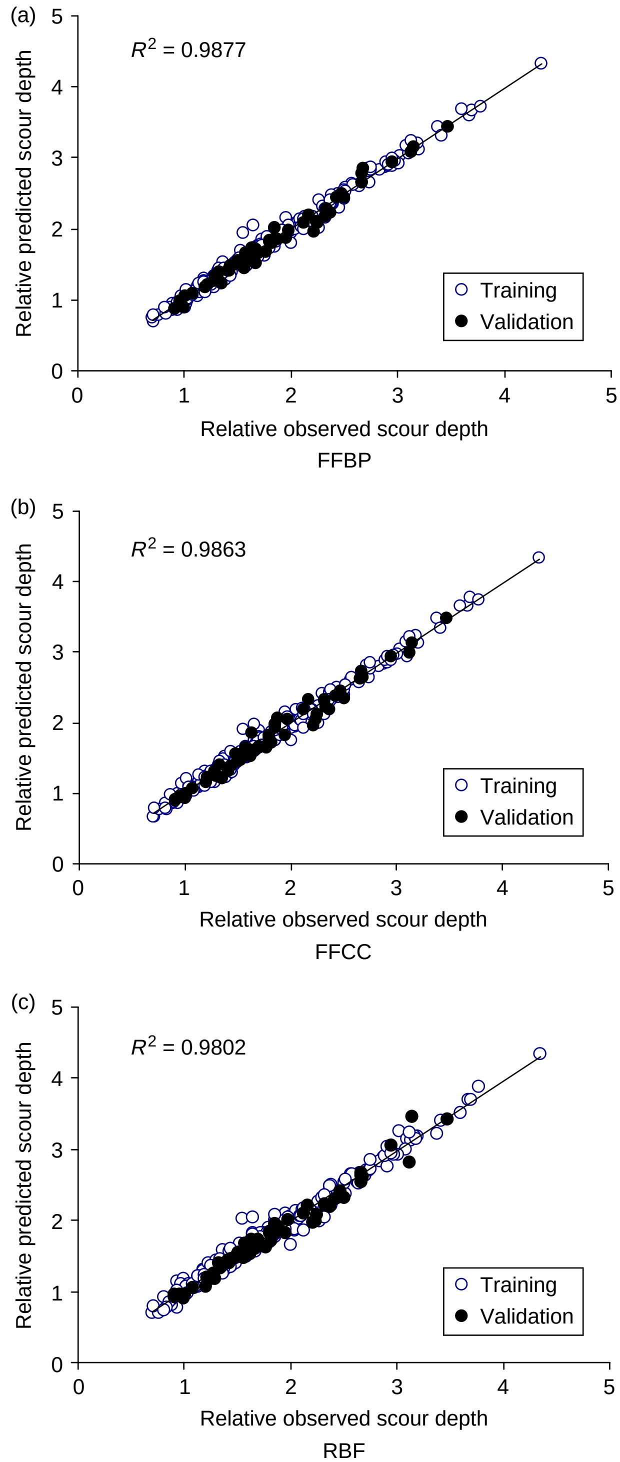

Figure 4 | A comparision of ANN models: (a) FFBP; (b) FFCC and (c) RBF.

Table 4 | Details of weights and biases for FFBP network

Weights					**Biases**	
Input				**Output**	**Input**	**Output**
1.641	−0.525	0.680	−0.756	0.462	−3.049	−0.321
−0.380	−1.921	−3.661	−9.680	−0.038	−3.495	
4.394	1.253	−2.656	6.933	0.022	−7.552	
3.285	7.721	−2.633	−0.958	−0.087	1.801	
4.830	−1.533	4.846	3.134	−0.063	−2.319	
4.623	−2.150	1.812	0.625	0.355	−0.456	
3.821	−1.976	−0.836	−3.992	−0.154	4.389	
−2.212	0.059	−1.139	−0.072	0.489	−1.086	
0.039	0.022	−0.232	0.158	4.389	−0.766	
−5.688	0.269	−1.423	1.184	−0.292	−0.503	
−0.133	−0.648	−0.127	0.156	−4.178	−1.872	
−2.685	0.406	−5.112	1.3742	−0.231	−1.866	

The clustering of numerical data forms the basis of many classification and system modelling algorithms. The purpose of clustering is to identify natural groupings of data from a large dataset to produce a concise representation of system behaviour. The Fuzzy Logic Toolbox is equipped with some tools that allow us to find clusters in input-output training data. We can use the cluster information to generate a Sugeno-type fuzzy inference system that best models the data behaviour using a minimum number of rules. The rules partition themselves according to the fuzzy qualities associated with each of the data clusters.

The optimum value of cluster radius was determined by trial and error based on the criterion of maximum correlation coefficient and minimum root mean square error. The optimal radius of cluster was found to be 0.40.

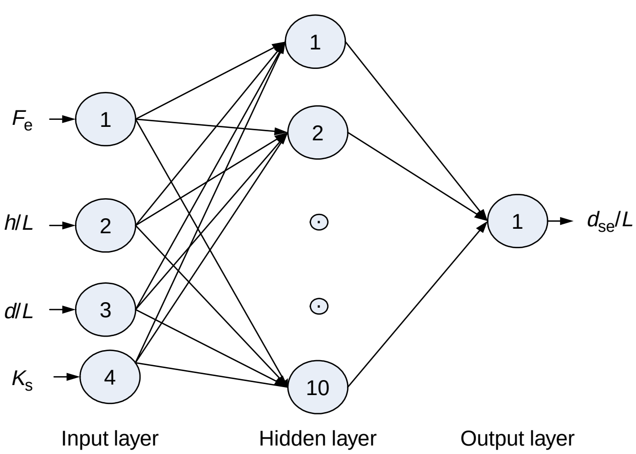

Figure 5 | Architecture of Feed Forward Back Propagation algorithm (FFBP).

Figures 6 and 7 depict the details of the membership functions (MFs). The initial and final MFs of each of the input parameters (F_e, L/y, d/L, K_s) may be compared with each other. Observe that there is a drastic change in the shapes of F_e as compared to other parameters. The change in the shapes of MFs for an input after training reflects its influence on the output.

A summary of the results of the ANFIS model are given in Table 5. It may be observed that eight fuzzy rules correspond to the cluster radius of 0.40. The performance of the ANFIS was assessed and performance indices are given in Table 6 for training as well as validation processes. Figure 8 depicts a scatter diagram of the relative observed and predicted scour depths for ANFIS model. It can be clearly observed that the performance for the ANFIS-based modelling is satisfactory and better in training as well as validation.

An overall assessment of the various scour depth prediction models has also been made. This is to assess the performance of the ANFIS model over other scour prediction models.

Table 7 shows the details of the performance indices of the various models under consideration for training as well as validation of datasets. It may be observed that the performance of ANFIS is the best among the prediction

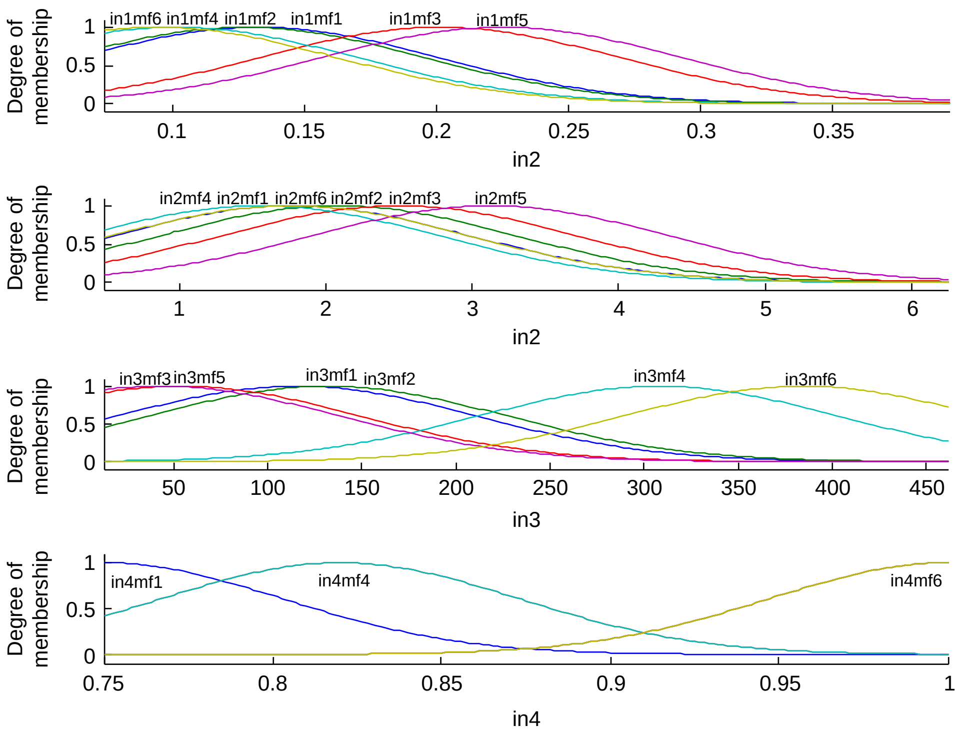

Figure 6 | Initial membership functions for inputs (in1 = F_e; in2 = h/L; in3 = d/L and in4 = K_s; D_m = Degree of membership).

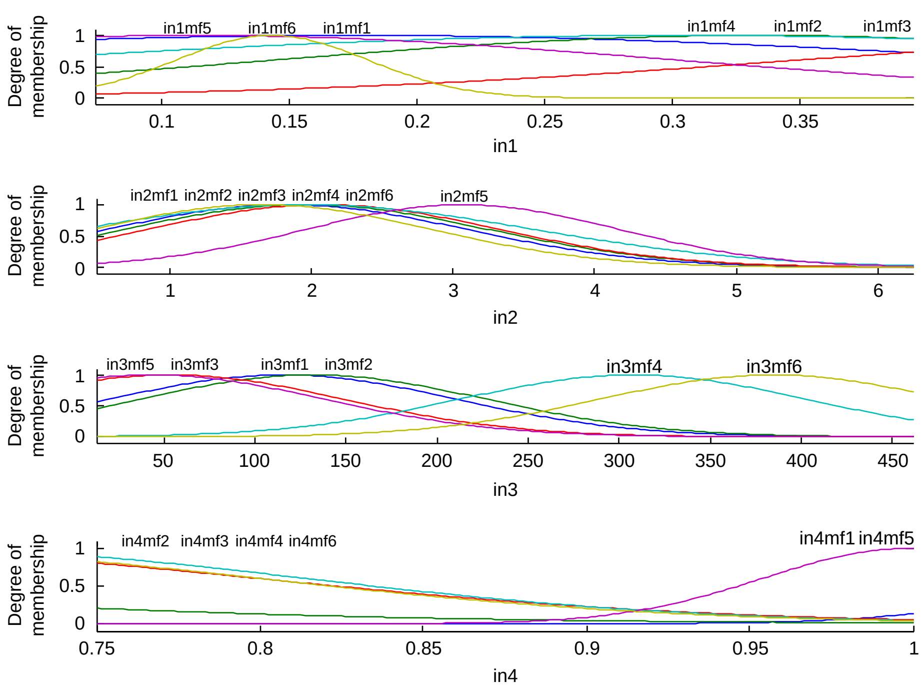

Figure 7 | Final membership functions for inputs (in1 = F_e; in2 = h/L; in3 = d/L and in4 = K_s; D_m = Degree of membership).

Table 5 | Summary of the results for ANFIS model for dimensionless parameters

Item	Parameters	Details
1	Number of nodes	70
2	Number of linear parameters	32
3	Number of nonlinear parameters	48
4	Total number of parameters	80
5	Number of training data pairs	162
6	Number of checking data pairs	41
7	Number of fuzzy rules	8
8	Cluster radius	0.4

Table 6 | Performance of ANFIS model for scour depth prediction at the abutments

Stages	*R*	mape	rmse
Training	0.99	2.571	0.057
Validation	0.99	3.020	0.072

models under consideration. It shows that the ANFIS-based treatment to non-linearities in the scour data worked much better than other approaches. It also leads to the conclusion that the scour data of the bridge abutments are more amenable to fuzzy if-then rules rather than crisp processing. The ANFIS ensures localized functioning of the transfer function as against the globalized function of a general FFBP, resulting in a smaller number of values particularly in the mapping process; the ANFIS may therefore work well with limited data for training.

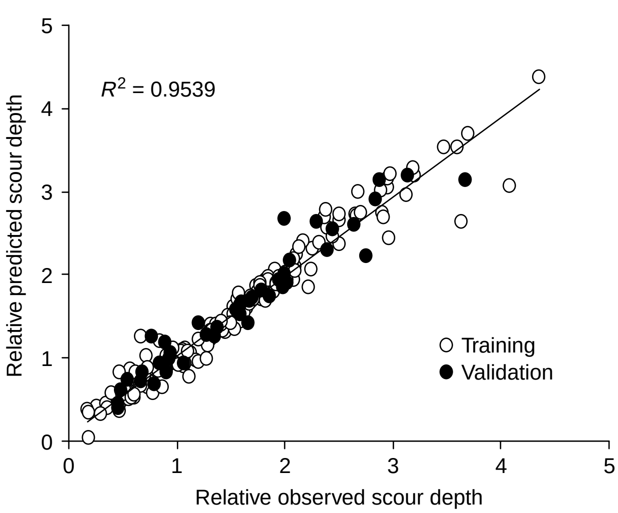

Figure 8 | Scatter diagrams of relative observed and predicted scour depths for ANFIS model.

Table 7 | A comparative assessment of various models of scour depth prediction

	Performance of models during training			Performance of models during validation		
Models	*R*	mape	rmse	*R*	mape	rmse
RM	0.97	7.700	0.157	0.97	6.452	0.142
ANN	0.99	3.290	0.075	0.99	3.228	0.079
ANFIS	0.99	2.571	0.057	0.99	3.020	0.072

ANFIS models for scour depth prediction using original dataset

The pattern of the data presented for the training is considered to be one of the important aspects of the ANFIS network approach. In this case, the ANFIS along with a subtractive clustering method was used for the scour depth prediction with the excess approach velocity (U_e), the abutment length (L), flow depth (h), sediment size (d) and shape factor (K_s) as inputs and the scour depth (d_{se}) as output.

Details of the parameters for the ANFIS model for raw data are provided in Table 8. A comparison of model performance based on grouped data and raw data is provided in Table 9. A close inspection of this table indicates that the raw data provides a better performance than that of non-dimensional parameters. These results are in line with those of Bateni *et al.* (2007*a*).

Table 8 | Summary of the results for ANFIS model for dimensional parameters

Parameters	Details
Number of nodes	68
Number of linear parameters	30
Number of non-linear parameters	50
Total number of parameters	80
Number of training data pairs	237
Number of checking data pairs	59
Number of fuzzy rules	5
Cluster radius	1.00

Table 9 | Performance of ANFIS model for the grouped and raw data

	Training stage			Validation stage		
Variable	*R*	mape	rmse	*R*	mape	rmse
Grouped	0.99	2.571	0.057	0.99	3.020	0.072
Original	0.99	1.917	0.003	0.99	2.237	0.004

CONCLUSIONS

An attempt was made to assess the performance of the various predictions of RM, ANN and ANFIS using an adequate volume of laboratory data for scour depth at the bridge abutments.

In the case of ANN models, FFBP training algorithm was found to be the best among the other training algorithms. The performance of ANN with all three training algorithms (FFBP, FFCC and RBF) was found to be better than that of the regression method.

As far as the performance of the ANFIS model is considered, it was found to be best between the regression model and the artificial neural networks model. These results indicate that the ANFIS-based treatment to non-linearity in the scour data worked much better than other approaches. As such, the scour data of the bridge abutments appear to be more amenable to fuzzy if-then rules rather than crisp processing. Further, it was found that the ANFIS approach predicts scour depth better when trained with raw data rather than grouped data.

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