

Prediction of Scour Around Hydraulic Structure Using Soft Computing Technique

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Abstract

The problem of accurate prediction of the depth of scour around hydraulic structure (trajectory spillways) has been based on the experimental studies and the equations developed are mainly empirical in nature. This paper evaluates the performance of the soft computing techniques, Adaptive Neuro-Fuzzy System (ANFIS), in prediction of scour around hydraulic structure. The results are very promising, which support the use of these intelligent techniques in prediction of highly non-linear scour parameters.

1. Introduction

Spillways provide for disposal of flood water in excess of the reservoir capacity and also lead to the control of water flow at the downstream. Out of several types of spillways the over-fall, ogee and breast wall spillways are more commonly used. The energy dissipation in such spillways can be in the form of ski-jump jet, which throws the water jet away from the bucket lip into the air, and then in the plunge pool formed at the point of impact on the tail water. The impact of the high velocity jet gives rise to the scour both upstream and downstream of the point of impingement. Such impact is transmitted through cracks and fissures of the rock by way of hydrodynamic pressure fluctuations causing hydraulic jacking action and also by the transient pressure fluctuation caused due to air locking. This causes the rock mass to break into small pieces and to consequently get swept away in the downstream of the river. The erosion continues up to the point where the impinging jet energy is insufficient to exert breaking pressure on the rock or where the secondary current produced are less strong to remove the rock blocks (Mason and Arumugam, 1985).

The depth of scour is governed by a number of hydraulic, morphologic and geotechnical factors like (refer Fig 1) discharge intensity q , height of fall H_1 , bucket radius R , bucket lip angle, ϕ , tail water depth d_w , type of rock, size of rock d_{50} , degree of rock homogeneity, time and mode of operation of spillway. (Azmathullah, 2005). In order to determine the safety of the dam and the adjoining

structures, it is necessary to estimate the depth of the scour hole formed.

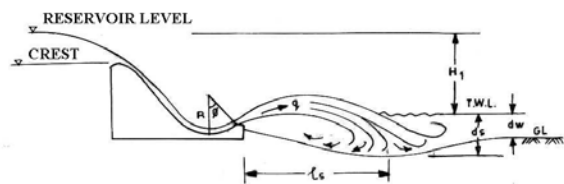


Fig.1: Scour below trajectory bucket spillway

A number of empirical formulas are available for scour depth estimation, like Veronese (1937), Damle et al.(1966), Wu (1973), and Lopardo et al. (2002). However, the problem of scour prediction has remained inconclusive; the main reason being the complexity of the phenomenon. Azmathullah (2005) has demonstrated the use of artificial neural networks for the scour estimation, which has many advantages over the conventional statistical analysis.

In this study, the use of artificial neural networks - neuro fuzzy models is demonstrated for the estimation of spillway scour. ANFIS models have additional advantages like faster training compared to artificial neural network (ANNs), and transparent results which can be easily understood by the decision makers. This study is aimed at knowing how it performs compared with ANN and regression equations (Azmathullah 2005) in estimating the spillway scour.

The data used for the study is obtained from Azmathullah (2005), who has compiled measurements from numerous hydraulic model studies conducted in India. Table 1 gives the entire range of various parameters collected from the past as well as present hydraulic model studies.

Table 1 Range of experimental data

Sl.No.	Parameter	Units	Range
1	Discharge intensity, q	m ³ /s/m	0.0089-0.3810
2	Total head, H ₁	m	0.2791-1.7962
3	Bucket radius, R	m	0.1000-0.6096
4	Lip angle, φ	radians	0.1740-0.7800
5	Tail water depth, d _w	m	0.0286-0.2650
6	Bed material size, d ₅₀	m	0.0020-0.0080
7	Depth of scour, d _s	m	0.0512-0.5500
8	Distance of maximum scour from bucket lip, ℓ _s	m	0.4200-2.2400
9	Width of scour hole, w _s	m	0.6000-2.1400

2. Dimensional Analysis

Referring to the Fig.1 the equilibrium depth of scour (d_s), measured from tail water surface, can be written as a function of discharge per m width or unit discharge of spillway (q), total head (H₁), radius of the bucket (R), lip angle of the bucket (φ), tail water depth (d_w), mean sediment size (d₅₀), acceleration due to gravity (g), densities of water and sediment, ρ_w and ρ_s.

$$d_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \quad (1)$$

In the present study the standard deviation of fragmented bed material σ_g has not been considered.

The maximum width of scour hole (w_s) and the distance of maximum scour depth from spillway bucket lip (ℓ_s) can be written in a similar form as,

$$\frac{d_s}{d_w} = 6.914 \left(\frac{q}{\sqrt{gd_w^3}} \right)^{0.694} \left(\frac{H_1}{d_w} \right)^{0.0815} \left(\frac{R}{d_w} \right)^{-0.233} \left(\frac{d_{50}}{d_w} \right)^{0.196} (\phi)^{0.196} \quad (7)$$

$$w_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \quad (2)$$

$$\ell_s = f(q, H_1, R, \phi, d_w, d_{50}, g, \rho_w, \rho_s) \quad (3)$$

By the use of the Buckingham π theorem, non-dimensional equations in functional form can be obtained, as below:

$$\frac{d_s}{d_w} = f \left(\frac{q}{\sqrt{gd_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi \right) \quad (4)$$

$$\frac{w_s}{d_w} = f \left(\frac{q}{\sqrt{gd_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi \right) \quad (5)$$

$$\frac{\ell_s}{d_w} = f \left(\frac{q}{\sqrt{gd_w^3}}, \frac{H_1}{d_w}, \frac{R}{d_w}, \frac{d_{50}}{d_w}, \frac{\rho_s}{\rho_w}, \phi \right) \quad (6)$$

Above functional relationships have been worked out in the present study, in which the ratio of sediment density to water density, ρ_s/ρ_w would be constant for a given bed material sample being used in the experiments and can be eliminated from the analysis.

3. Statistical Regression Models

In this study, the above mentioned dimensionless groups of parameters have been related to each other on the basis of non-linear regression. This yielded following equations for estimating maximum scour depth, maximum scour width and distance of maximum scour location respectively:

Eighty percent of observations have been used to arrive at expressions for predicting the equilibrium scour hole parameters, according to the functional relationship given by equations (4) to (6). The following equations are obtained for estimating maximum scour depth, maximum scour width and distance of maximum scour point (location) respectively by using the non-linear regression analyses:

$$\frac{\ell_s}{d_w} = 9.85 \left(\frac{q}{\sqrt{gd_w^3}} \right)^{0.42} \left(\frac{H_1}{d_w} \right)^{0.28} \left(\frac{R}{d_w} \right)^{0.043} \left(\frac{d_{50}}{d_w} \right)^{0.037} (\phi)^{0.34661} \quad (8)$$

$$\frac{w_s}{d_w} = 5.42 \left(\frac{q}{\sqrt{gd_w^3}} \right)^{-0.015} \left(\frac{H_1}{d_w} \right)^{0.55107} \left(\frac{R}{d_w} \right)^{0.1396} \left(\frac{d_{50}}{d_w} \right)^{0.242} (\phi)^{-0.16} \quad (9)$$

The constants in the above equations have been worked out on the basis of the least square fit to 80% of randomly selected values. Use of the Origin software in windows platform has been made for this purpose.

4. Implementation of the ANFIS Model

The MATLAB computing language is utilized for model programming. Since the ANFIS is usually started with a prototype fuzzy system, a fuzzy system generator is needed. The software MATLAB (Mathworks Inc., USA) also provides three fuzzy system generators ready for use, i.e. “fuzzy”, “genfis1” and “genfis2”. If explicit knowledge of the system is available, designers can directly create a fuzzy system using “fuzzy” function. If it is not clear what the fuzzy system should look like, it can be started using either “genfis1” or “genfis2” provided a training data set is available. The function “genfis1” can examine the data set and then generate a fuzzy system based on the given numbers and types of membership functions. In some cases, designers have no idea of the numbers and types of membership functions. The function “genfis2” would generate a first order Sugeno fuzzy system based on subtractive clustering of the data set provided (Tay and Zhang, 1999).

After the input and output parameters were determined, genfis2 was employed to generate first order Sugeno fuzzy system (Fig. 2) and the ANFIS architectures are similar as they have the same number of inputs and rules. Fig. 5.16 depicts the schematic structure of ANFIS model Ds. In order to map the causal relationship related to the scour input-output scheme were employed, where utilized their non-dimensional groupings. Model d_s (Fig. 2) employs the input of grouped dimensionless variables namely, F₀, H₁/d_w, R/d_w, d₅₀/d_w and φ (F₀ being q/(g d_w³)^{1/2}) and so also the output of relative scour depth, length and width, i.e., d_s/d_w, l_s/d_w, w_s/d_w respectively.

Similar to the regression exercise described earlier, out of the total of 95 input-output pairs, 80

percent, selected randomly, were used for training and remaining 20 percent were employed for testing or validation, dictated by the use of Gaussian function all patterns were normalized within the range of (0.0, 1.0) before their use. The trainings of these networks were stopped after reaching the minimum error goal of 0.0005.

The performance of the model was assessed by evaluating the scatter between the observed and predicted results via correlation coefficients r, root mean squared errors (RMSE), the average error (+ or -), AE, and the average absolute deviation, δ. Comparison of ANFIS results with earlier ANN results (Azamathulla, 2005) like feed forward back propagation (FFBP2), feed forward cascade correlation (FFCC) and radial basic function (RBF2) (Table 2).

Figures 5.17 and 5.19 show a scatter diagram where the ANFIS based predictions of scour depth, width and length are compared with the target values for testing set. It may be seen that while depth is predicted with a good accuracy (r= 0.98) the width and length of scour are predicted, as earlier, with lesser accuracy and there is also a tendency to underestimate the medium level values; the reason for the latter observation is not clear.

It may be seen from Figures 3, 4 and 5 as well as Table 2 that when the scour depth alone is considered, ANFIS Model emerges as the most accurate model showing highest correlation (r = 0.976) and lowest difference between predicted and actual scour depths (AE = -0.09882 %, δ = 12.509 % and RMSE = 0.56921).

When it comes to length of the scour hole considerable variation in error measures across various networks may be noticed. In this case the FFBP; Model-2 comes out as most acceptable network in terms of accuracy as it involves highest r (=0.989) and lowest AE (=2.876%), δ = (3.725) and RMSE (=0.72041) values.

Examination of Table 2 for the case of width of scour hole suggests that there is a large variation in magnitudes of error measures across the neural networks and that the most accurate network is

again FFBP; Model-2, which has the highest r of 0.990 and lowest AE, δ and RMSE values of -2.336 %, 9.111% and 1.6723 respectively.

5. Conclusions:

The results were compared with the regression equation formulae and neural network schemes it was found that the ANFIS results are highly satisfactory, as seen from the Figures 3 through 5 shows a scatter plot for depth of scour downstream of flip bucket, width and location of maximum scour from bucket lip.

Further studies for obtaining the pattern of scour, So also its location with respect to bucket lip and with rock quality designation (RQD) for prototype data are in progress. The preliminary studies indicated very good prediction. As such it is concluded that ANFIS is more efficient in predicting scour parameters downstream of flip bucket to other neural network schemes.

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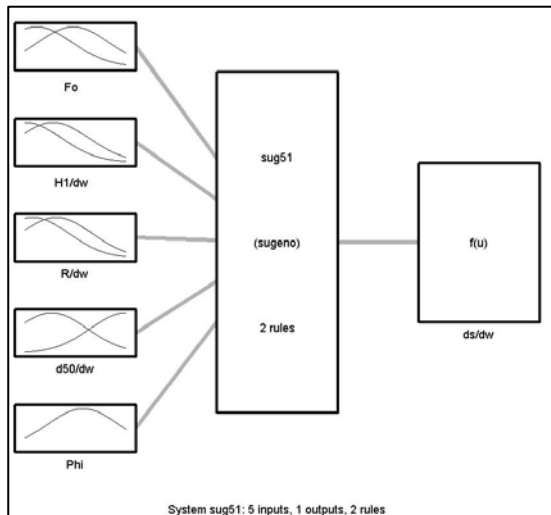


Fig. 2 The ANFIS Model for d_s/d_w

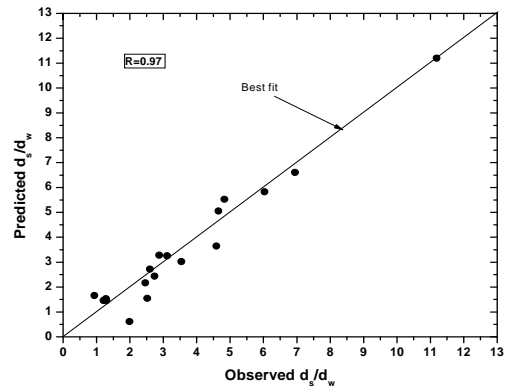


Fig. 3: Scatter diagram of observed versus predicted values of the relative scour depth

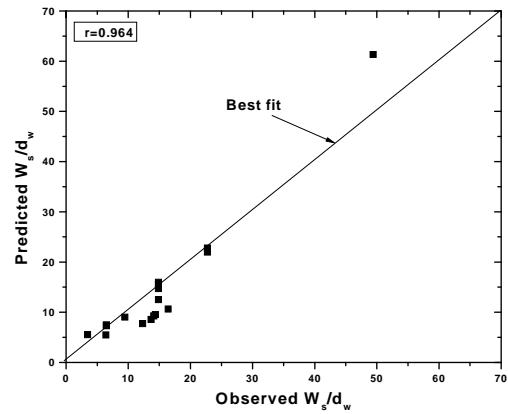


Fig. 4: Scatter diagram of observed versus predicted values of the relative scour width

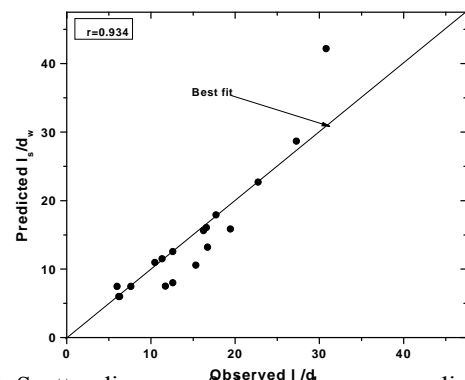


Fig. 5: Scatter diagram of observed versus predicted values of the relative scour length (distance from bucket lip)

Table 2 : Comparison of network – yielded and true values

Parameter	R	AE	δ	RMSE
ANFIS-Model				
ds / dw	0.976	-0.09882	12.50924	0.56921
fs / dw	0.936	4.849	14.116	3.515679
ws / dw	0.965	4.6170	18.340	3.995247
Regression Equations				
ds / dw	0.842	-1.427	22.790	1.343503
fs / dw	0.929	3.900	13.550	3.569314
ws / dw	0.883	-19.570	20.150	5.612486

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Appendix I

The Error Measures

Correlation coefficient (r),

$$r = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}}$$

Where $x = (X - \bar{X})$, $y = (Y - \bar{Y})$, $X =$
Observed values, $\bar{X} =$ Mean of X, $Y =$ Predicted
value, $\bar{Y} =$ Mean of Y. The summation in the above
equation as well as in the following two equations is
carried out over all 'n' number of testing patterns.

Average error (AE),

$$AE = \frac{\sum \frac{X - Y}{X} * 100}{n}$$

Root Mean Square Error (RMSE),

$$RMSE = \left[\frac{\sum (X - Y)^2}{n} \right]^{\frac{1}{2}}$$

Average absolute deviation, δ :

$$\delta = \frac{\sum |(Y - X)|}{\sum X} * 100$$