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Modeling Local Scour on Loose Bed Downstream of Grade-Control Structures Using Artificial Neural Network

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Abstract: The study describes the application of the Artificial Neural Networks (ANNs) to predict local scour downstream of a grade-control structure. Four important dimensionless parameters, including: the ratio of the maximum scour depth to the height of structure (s/z), the ratio of distance of maximum scour from structure to z (XS/z), the ratio of distance of maximum deposit mound to z (SD/z) and the ratio of maximum height of dune to z (h_d/z) have been modeled using ANNs. The scour measurements available in the literature were used to establish and verify the ANNs models. The final models for each scour variable parameters have been compared favorably with the recent experimental formulations published in the literature, describing the downstream scour of grade-control structures.

Key words: Grade-control structures, artificial neural networks, scour model, hydraulic structures stability

INTRODUCTION

Grade-control structures prevent excessive channel-bed degradation in alluvial channels, where the general bed slope is high. The local scour downstream of a grade-control structure, having a weir width b and a fall height z (Fig. 1), located on an alluvial bed is a very complex phenomenon even in terms of estimating the potential maximum erosion depth. Determination of scour location and depth is necessary to design of foundation and to prevent destruction of structure. A number of attempts have been made to relate the local scour downstream of grade control structures with various hydraulic and morphological factors, e.g., water discharge, fall height, weir width, median bed particle size and mass density of sediments. Various investigators over a period of several decades in the past have given empirical formulas based on laboratory as well as prototype observations in order to predict the scour downstream of a grade-control structure. However, these techniques may not be adequate in view of such complex phenomenon. In this study the local scour downstream of a grade-control structure has been modeled using a powerful engineering tool, i.e., Artificial Neural Networks (ANNs).

More than 50 years of laboratory measurements of scour depths under various flow conditions and structure configurations are available in the literature. Significant studies of local scour under a free jet downstream of hydraulic structures include those of Damle *et al.* (1966), Smith and Strang (1967), Chee and Padiyar (1969), Chee and Kung (1971), Chee *et al.* (1972), Martins (1975), Laursen and Flick (1983) and Akashi and Saitou (1986). Maximum scour-depth equations were typically obtained from small-scale laboratory experiments with unit discharges less than 0.093 $m^2\ sec^{-1}$ and scour depth not exceeding 0.8 m. A large-scale model research carried out by Bormann and Julien (1991) enabled the calibration of an equilibrium equation based on particle stability and its validation in a wide range of conditions, including: vertical jets, wall jets, free jets, submerged jets and flow over large-scale grade-control structures. In their research, unit discharges were ranging from 0.30 to 2.5 $m^2\ sec^{-1}$ and maximum scour depth reaching up to 1.4 m.

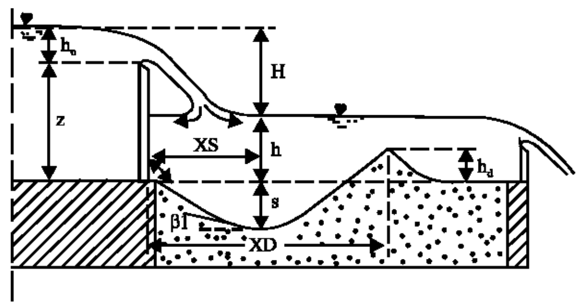

Fig. 1: Sketch of the scour of an alluvial bed downstream of a grade control structure

Mason and Arumugam (1985) tested some formulas of scours under free-falling jets using model and prototype data. The authors obtained the best agreement

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between the selected equations and measurements for the model data using a representative diameter of d_s (m) equal to the mean particle size d_m. The authors proposed a comprehensive model and prototype equation, which can be rewritten, according to the suggestions of Yen (1987), in the following form:

$$\frac{s}{\left(\frac{q^2}{g}\right)^{1/3}} = \left(6.42 - 3.10H^{0.1}\right)g^{-H/600}\left(\frac{gH^3}{q^2}\right)^{20+H/600}\left(\frac{H}{d_s}\right)^{1/10}\left(\frac{h}{H}\right)^{3/20} \quad (1)$$

Where:

s = Maximum scour depth (m)
g = Acceleration due to gravity (m sec^{-2})
H = Difference in height (m) between upstream and tail water level
q = Water discharge per unit weir width

Mason and Arumugam (1985) advised that d_s (m) to be equal to the mean particle size d_m in Eq. 1 for models, while a constant value of the representative diameter, equal to 0.25 m, was suggested for predicting scours on prototypes.

D`Agostino and Ferro (2004) used the incomplete self-similarity (ISS) theory and some experimental scour depth data to establish some relationships describing the geometrical pattern of the scour profile including: maximum scour depth, horizontal distance between the weir crest and the section of maximum scour depth, horizontal distance between the weir crest and the dune crest (s, XS and XD in Fig. 1, respectively). All these data refer to a null bed slope of the downstream channel, no sediment feeding upstream of the grade-control structure and to the absence of interference between the scour and the gate or the transversal structure controlling the tail water depth.

The relationship for estimating the maximum scour depth was defined as:

$$\frac{s}{z} = 0.540\left(\frac{b}{z}\right)^{0.593}\left(\frac{h}{H}\right)^{-0.126}\left(A_{50}\right)^{0.544}\left(\frac{d_{90}}{d_{50}}\right)^{-0.856}\left(\frac{b}{B}\right)^{-0.751} \quad (2)$$

The local bed degradation caused by the entering jet modifies the point where the jet impacts against the bed respect to the fixed bottom conditions. This position also becomes important to define the upstream face slope of the profile of hole. D`Agostino and Ferro (2004) used the statistical analysis, carried out by forward stepwise regression procedures (logarithms of data), to describe the location of maximum scour. According to their suggestions, the relationship for estimating XS has the following form:

$$\frac{XS}{z} = 1.616\left(\frac{b}{z}\right)^{0.662}\left(\frac{h}{H}\right)^{-0.117}\left(A_{90}\right)^{0.455}\left(\frac{b}{B}\right)^{-0.478} \quad (3)$$

Position and height of the dune downstream of the pool (XD and h_d in Fig. 1) are the most useful parameters for designing a subsidiary transversal structure able to induce a steady-state scour profile during flood events. D`Agostino and Ferro (2004) also deduced equations for predicating XD, where the crest dune is located and the dune height h_d, which is above the original bed level. Experimental data of D'Agostino (1994) were analyzed for calibrating predictive equations. The analysis was carried out using the ISS approach, which warrants stronger scale invariance than that of the relationships previously inferred by D'Agostino (1994). Equations have the following forms:

$$\frac{XD}{z} = 5.828\left(\frac{b}{z}\right)^{0.241}\left(\frac{h}{H}\right)^{0.041}\left(A_{50}\right)^{0.508}\left(\frac{d_{90}}{d_{50}}\right)^{-1.077}\left(\frac{b}{B}\right)^{0.057} \quad (4)$$

$$\frac{h_d}{z} = 2.780\left(\frac{h}{H}\right)^{0.061}\left(A_{90}\right)^{0.764}\left(\frac{d_{90}}{d_{50}}\right)^{-2.489}\left(\frac{b}{B}\right)^{0.794} \quad (5)$$

In Eq. 2-5:

$$A_{50} = \frac{Q}{bz\left[gd_{50}\left(\frac{\rho_s - \rho}{\rho}\right)\right]^{1/2}}$$

Where:

h = Tail water depth (Fig. 1)
b = Weir width
B = Channel width
Q = Water Discharge
ρ = Mass density of water
ρ_s = Mass density of sediment
d_{50} = Diameter for which 50% of particles are finer
d_{90} = Diameter for which 90% of particles are finer

ARTIFICIAL NEURAL NETWORKS

Recent research studies in ANNs have shown that ANNs are able to provide powerful tools in forecasting dependent variables for a wide range of scientific and engineering problems. Currently ANNs are used for a very wide variety of tasks in many different fields of business, industry and science (Widrow *et al.*, 1994). Neural networks provide a random mapping in between an input and an output vector by mimicking the biological cognition process of our brain (Azmathullah *et al.*, 2005). An ANN consists of a number of data processing elements, called neurons or nodes that are grouped in layers. The input layer neurons receive the input vector and transmit the values to the next layer of processing elements across connections. This type of network, in which the data flows in one direction, is known as a feed-forward network (Zhang *et al*., 1998). A typical feed-forward ANN would consist of three layers of neurons namely, input, hidden and output, with each neuron acting as an independent computational element. It means each neuron in a layer is connected to all of the neurons of the next layer, but the neurons in one layer are not connected among themselves. The data passing through the connections from one neuron to another are multiplied by the weights that control the strength of the passing signal. When these weights are modified, the data transferred to the next layer are changed and as a result the network output node(s) will be changed. Each input value is multiplied by its interconnection weight and then the sum of the product for the all nodes in the first layer is transferred by a special function to produce the value of a node for the next layer. The most common transfer function is the S-shape curve, called a sigmoid function. There is no restriction on the input value to this function and the output value is always between 0 and 1. The sigmoid function for each node can be written as (Pham and Liu, 1999):

$$y_j = f\left(\Sigma w_{ji} x_i\right) = \frac{1}{1+e^{-(\Sigma w_{ji} x_i)}} \tag{6}$$

Where:

w_{ji} = Weight of the connection joining the j^{th} node in a layer with the i^{th} node in the previous laye

x_i = Value of the i^{th} node in the previous layer

The network has to be first trained using the series of data. Training comprises presentation of input and output pairs to the network and fixing the values of connection weights, bias or centers. The training may require many epochs (presentation of complete data sets once to the network). Generally, the network is presented with the input and output pairs until the training sum-square error reach the error goal in order to give the desired network performance. Details of concepts involved in neural networks along with their applications in water resources can be seen in the ASCE Task Committee (2000), Maier and Dandy (2000) and Dawson and Wilby (2001).

MODEL DEVELOPMENT

The scour phenomena due to the erosive action of flowing water can be related to the flow properties, hydraulic characteristics and channel geometry. It can be therefore mathematically written as (D`Agostino and Ferro, 2004):

$$y = f\left(z, b, B, h, Q, \rho_s, \rho, g, d_{50}, d_{90}\right) \tag{7}$$

In which: y = scour variable, e.g., maximum scour depth s or its horizontal abscissa XS (Fig. 1). Other parameters have been already explained. In the current research, to predict local scour downstream of grade control structures four parameters including: maximum scour depth s, horizontal distance between the weir crest and the section of maximum scour depth XS, horizontal distance between the weir crest and the dune crest XD and maximum height of the mound above the undisturbed bed level h_d have been selected. In order to establish a model for each variable using ANNs, the following dimensionless parameters were produced using the hydraulic elements in Eq. 7.

To model maximum scour depth s and horizontal distance between the weir crest and the section of maximum scour depth XD, five dimensionless key parameters were produced. These dimensionless parameters were: the weir width to a fall height b/z, tail water depth or water depth above the unerloaded bed level to difference in height h/H; A_{50}, the ratio d_{90}/d_{50} and the ratio b/B. D`Agostino and Ferro (2004) pointed out that the influence of d_{90} on affecting the abscissa XS and h_d is larger than d_{50}. Therefore to model horizontal distance between the weir crest and the section of maximum scour depth and maximum height of the mound above the undisturbed bed level these dimensionless are selected: (b/z), (h/H), A_{90} and (b/B) for XS and (h/H), (b/z), A_{90}, (d_{90}/d_{50}) and (b/B) for h_d. Due to the scour variable each group of dimensionless parameters was used in the input layer and one of the following dimensionless parameters is used in the output layer respectively: (s/z), (XD/z), (XS/z) and (h_d/z). To avoid localizing the training part of the each ANN model, only one hidden layer was considered for each dependent variable.

The laboratory selected experiments differ in their measured variables. To assess ANN dealing with the maximum scour depth available data of D'Agostino and Ferro (2004) and D'Agostino (1994) were used (182 sets of data). The measurements of XS, h_d, XD in the experimental runs of D`Agostino (1994) are also available and they have been used for these variables (114 sets of data). For all variables, from the data sets 70% of measurements were used for training, 20% of them were applied to validate the model and finally the rest of data were used to test and to compare the ANN model results with the recent favorable formulations published in the literature.

Three statistical methods were applied to assess the accuracy of the model predictions. These methods include:

Correlation coefficient: The Correlation Coefficient is defined as:

$$R^2 = \frac{\sum xy}{\sqrt{\sum x^2 \sum y^2}} \tag{8}$$

$$x = X_m - \bar{X}_m;\ y = X_p - \bar{X}_p$$

Where:
X_m = Measured value or the variable amount from exact solution
$\bar{X}_m$ = Mean of X_m
X_p = Predicted value by the appropriate model
$\bar{X}_p$ = Mean of X_p

Root Mean Square (RMS): This statistical criterion can be defined as:

$$RMS = \left[\frac{\sum (X_m - X_p)^2}{n}\right]^{1/2} \tag{9}$$

Where:
n = number of data

For accurate model predictions to be obtained then the resulting value for Eq. 9 should be as close as possible to zero.

The correlation coefficient and the value of α, as given by the following ratio:

$$\alpha = \frac{X_m}{X_p} \tag{10}$$

It is evident that for each model whenever the coefficient of α and the correlation coefficient are close to unity, then this will give rise to a more accurate prediction.

RESULTS AND DISCUSSION

Maximum scour depth (s): In order to predict maximum scour depth (s), five dimensionless parameters including: b/z, h/H; A_{50}, the ratio d_{90}/d_{50} and the ratio of b/B, were used in the input layer and dimensionless ratio of s/z was considered for the output layer. Several separate schemes were employed and finally the ANN model with 5 nodes in input layer and 7 nodes in the hidden layer together with the sigmoid transfer functions gives the best result. As can be seen from this Fig. 2 the model was able to accurately predict maximum scour depth. The correlation coefficients (R^2) for the training and validating patterns were 0.986 and 0.978, respectively.

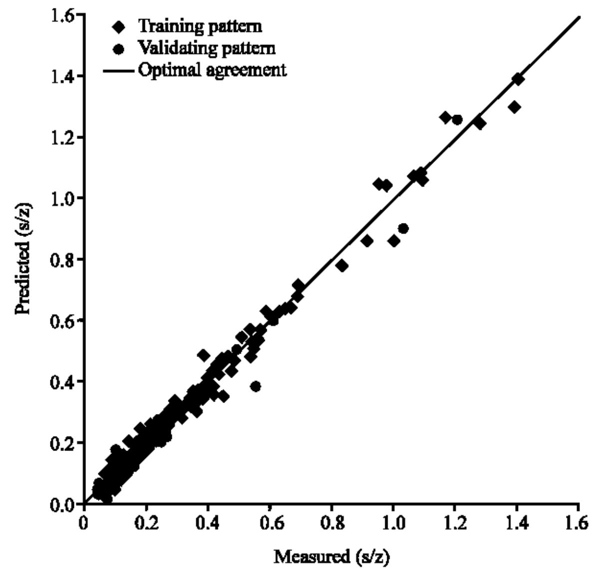

Fig. 2: Comparison of predicted and measured results for (s/z)

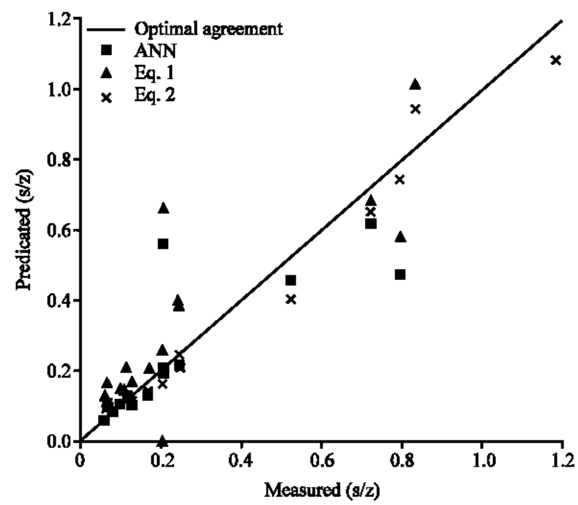

Fig. 3: Comparison of ANN results, computed values by Eq. 1 and 2 for (s/z) and measured values

The established model was applied with the rest of unused data in training and validating patterns for estimating the maximum scour depth and the model results were then compared with the corresponding predicted s/z values obtained using Eq. 1 and 2 in Fig. 3.

Table 1 shows comparison between accuracy of ANN model results and Eq. 1 and 2. As can be seen from this Table 1 the ANN model was able to predict the maximum scour depth more accurate than the other two recent experimental equations.

Location of the maximum scour (XS): The predicted ratio of XS/z is compared with the corresponding reference

Table 1: Comparison of various models using statistical analysis for (s/z)

Model	R^2	RMSE	α
ANN	0.880	0.144	0.980
Mason and Arumugam (Eq. 1)	0.750	0.196	1.003
D`Agostino and Ferro (Eq. 2)	0.771	0.183	0.889

Table 2: Comparison of various models using statistical analysis for (XS/z)

Model	R^2	RMSE	α
ANN	0.969	0.057	0.991
D`Agostino and Ferro (Eq.3)	0.802	0.465	1.437

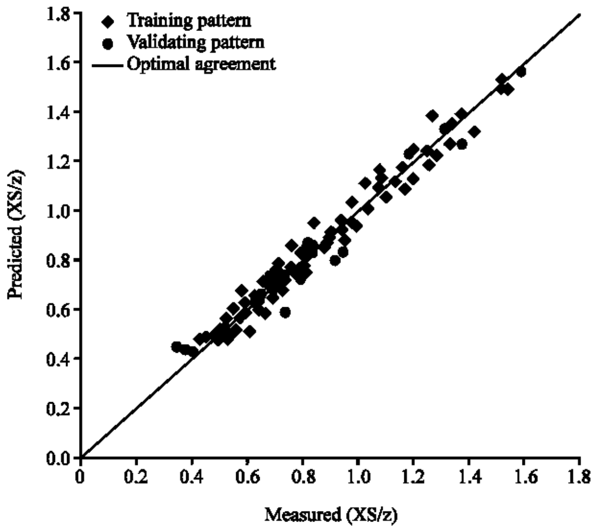

Fig. 4: Comparison of predicted and measured results for (XS/z)

values in Fig. 4. The correlation coefficient (R^2) for the training pattern was calculated to be 0.965 and for the validating pattern it was 0.965. To assess the established ANN model the rest of unused data (12 sets of data) have been applied and the obtaining results were compared with the corresponding values obtained from Eq. 3 suggested by D`Agostino and Ferro (2004) together with the measured values in Fig. 5. The correlation coefficient (R^2), root mean square (RMS) and the coefficient of α Eq. 10 were calculated for the predicted location of the maximum scour obtained using those models and are mentioned in Table 2. The comparison of results show that the accuracy of ANN model is much higher than the experimental equation suggested by D`Agostino and Ferro (2004).

Deposited mound: Two variables including: XD the crest dune position and the dune height h_d, which is above the original bed level are usually considered as two main parameters at the downstream of the eroded bed. Figure 6 and 7 show the patterns of the measured XD/z and h_d/z data against the corresponding predicted values, respectively. In modeling XD/z, the correlation

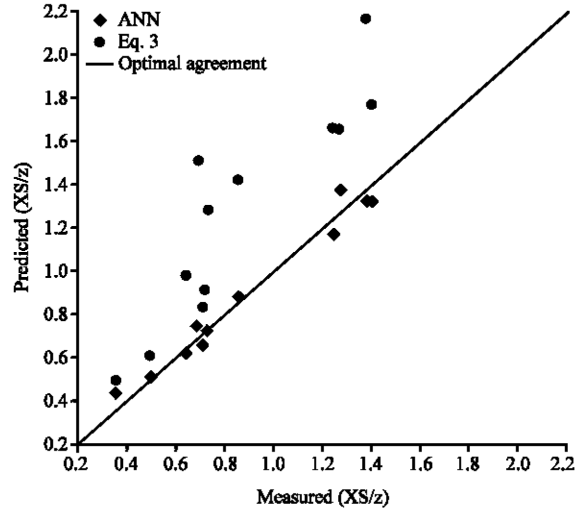

Fig. 5: Comparison of predicted and computed values by Eq. 3 for (XS/z)

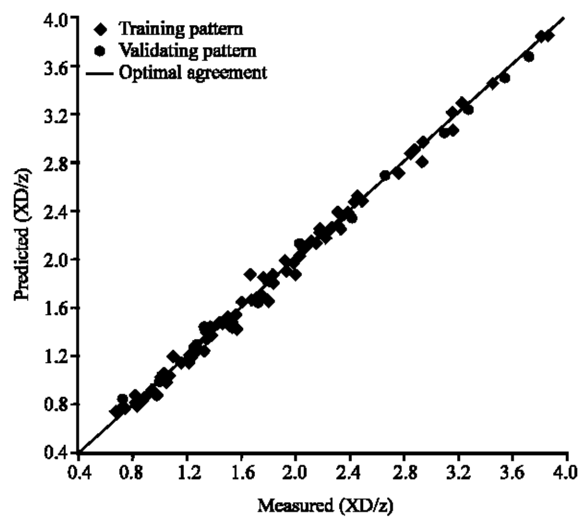

Fig. 6: Comparison of predicted and measured results for (XD/z)

coefficients (R^2) for the training and validating results were 0.994 and 0.995, respectively and for modeling dune height h_d, R^2 were obtained 0.989 and 0.983 for the training and validating patterns, respectively. These data show that the model was able to accurately predict deposited mound position.

The capability of the ANN models in accurately predictions of these two parameters was then tested against the rest of unused data sets in the training and validating patterns (12 sets of data from D`Agostino, 1994). The predicted (XD/z) and (h_d/z) values using these models were then compared with the corresponding

Table 3: Comparison of various models using statistical analysis

Dimensionless variable	Model	R^2	RMSE	α
XD/z	ANN	0.982	0.084	0.996
	D'Agostino and Ferro (Eq.4)	0.708	1.187	1.529
h_d/z	ANN	0.980	0.023	1.026
	D'Agostino and Ferro (Eq.5)	0.674	0.240	1.683

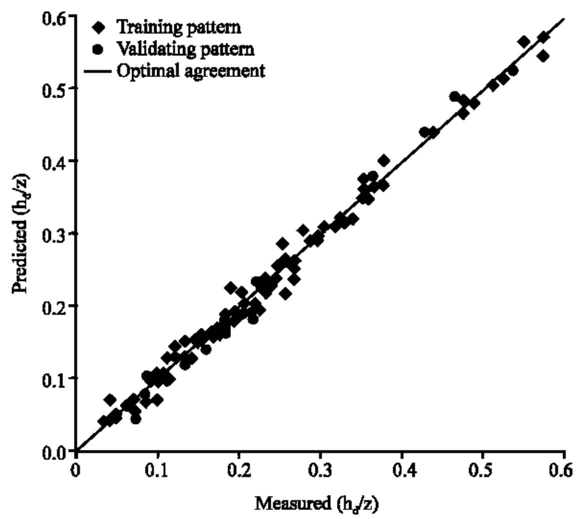

Fig. 7: Comparison of predicted and measured results for (h_d/z)

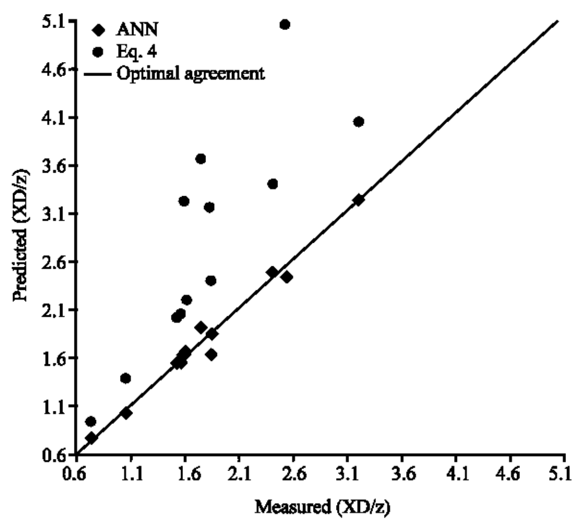

Fig. 8: Comparison of predicted and computed values by Eq. 4 for (XD/z)

measured values together with the results calculated from Eq. 4 and 5 and are shown in Fig. 8 and 9. The statistical parameters were also calculated and are mentioned in Table 3 for assessing the accuracy of models' predictions.

Table 3 shows that the ANN models established for predicting (XD/z) and (h_d/z) were more accurate than the

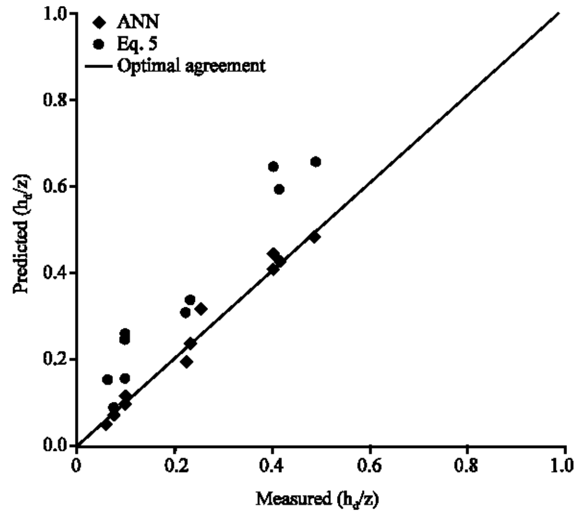

Fig. 9: Comparison of predicted and computed values by Eq. 5 for (h_d/z)

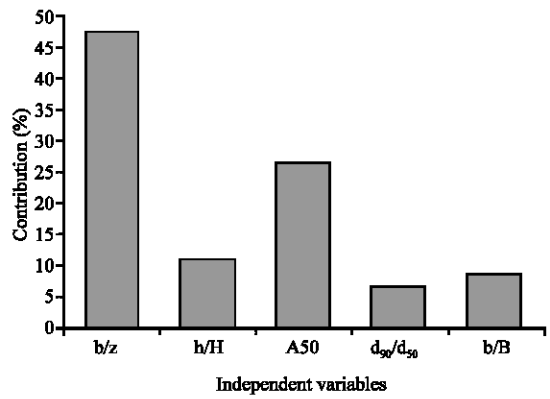

Fig. 10: Sensitivity analysis for (s/z)

other two equations considered. The α values in this table indicates that Eq. 4 and 5 generally overestimate the (XD/z) and (h_d/z) values, respectively.

In this research the sensitivity of each dependent variables in respect to the independent variables used in establishing the models were also analyzed. For the maximum relative scour depth (s/z), the ratio of weir width to the fall height (b/z) was found to be the most effective parameters in comparison with the other variables (Fig. 10). Figure 11 shows the percentage contributions of the dimensionless independent variables for establishing the ANNs model for the relative distance of maximum scour from structure (XS/z). As can be seen from this Fig. 11, (XS/z) showed the most sensitivity to A_{90}. The models of relative distance of maximum deposit mound (XD/z) and maximum height of dune (h_d/z) have had the

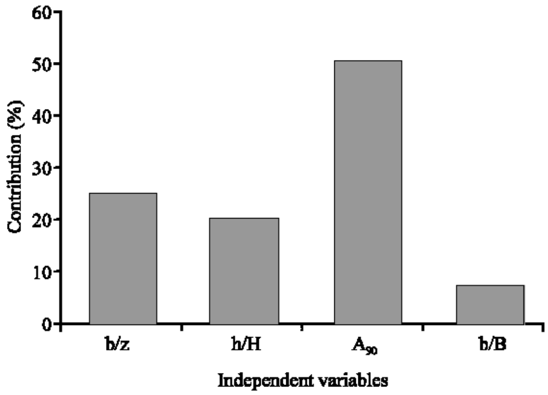

Fig.11: Sensitivity analysis for (XS/z)

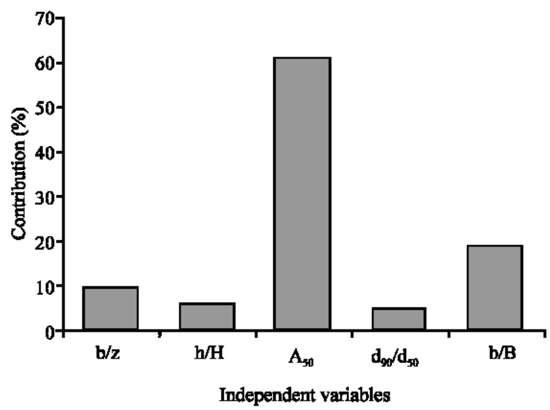

Fig. 12: Sensitivity analysis for (XD/z)

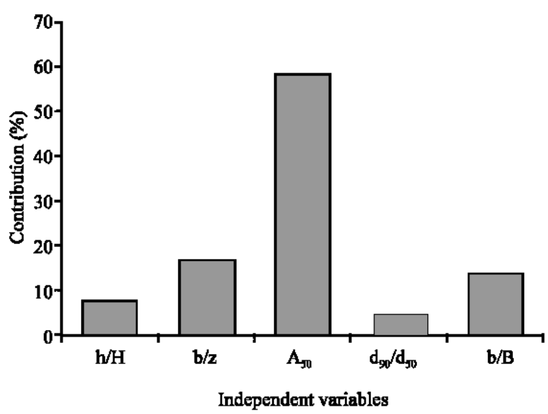

Fig. 13: Sensitivity analysis for (h_d/z)

most sensitivity to the A_{50} and A_{90} respectively. Results of the sensitivity analysis for the dependent variables including: (XD/z) and (h_d/z) are shown in the Fig. 12 and 13, respectively.

CONCLUSION

In this study, one of the most powerful engineering tools, artificial neural network (ANN) model was applied to predict the scour on bed downstream of grade-control structures. In these models the dimensionless scour variables (e.g., maximum scour depth s/z) were related to the main dimensionless hydraulic and channel geometry characteristics, such as: the ratio of weir width to fall height (b/z) and the ratio of tail water depth to the difference in height upstream and downstream of the wier (h/H). A total of 182 sets of measured data for the relative maximum scour depth (s/z) and 114 sets of data for the other dependent variables (XS/z, XD/z and h_d/z) were available from the current literature. After training and validating of ANN for each scour component, the models were satisfactory and successfully compared with the recent published experimental formulations, which are established using the measured values and traditional nonlinear regression analysis.

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