Chapter 11
Prediction of Local Scour Depth Downstream of Bed Sills Using Soft Computing Models

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Abstract Bed sill local scour is an important issue in environmental and water resources engineering in order to prevent degradation of river bed and save the stability of grade-control structures. This chapter presents genetic algorithms (GA), gene expression programming, and M5 decision tree model as an alternative approaches to predict scour depth downstream of bed sills. Published data were compiled from the literature for the scour depth downstream of sills. The proposed GA approach gives satisfactory results ($R^2 = 0.96$ and RMSE $= 0.442$) compared to existing predictors.

Keywords Grade-control structures • Local scour • Genetic algorithms • M5 tree decision model • Gene expression programming

11.1 Introduction

Bed sills are a common solution to stabilize degrading bed rivers and channels. They are aimed at preventing excessive channel-bed degradation in alluvial channels. Although their presence limits the general erosion process in the upstream, but the erosive action of the weir overflow and turbulence generated from plunging jet may cause significant local scour at downstream. By this local scour, the structure itself (and many times other structures in vicinity of it, like bridge piers or abutments, or bank revetments) might be undermined (Bormann and Julien 1991; Gaudio and Marion 2003).

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For practical purposes, designers and civil engineers are often interested in a short-term local scouring and its extent. For instance, they are often required to predict the maximum scour depth at bed sills in the proximity of bridges when a flood occurs. Therefore, most researchers have focused on local scouring at isolated or series bed sill structures. Summaries of research for the bed sills can be found in Lenzi et al. (2002). Bormann and Julien (1991) reviewed experimental studies of scour downstream of hydraulic structures. They also investigated the scour downstream of grade-control structures with large-scale experiments. Gaudio et al. (2000) presented a theoretical framework for calculation of maximum scour depth downstream of bed sills through identification of non-dimensional parameters by Buckingham's π-theorem. They proposed an empirical equation for the estimation of maximum scour depth at bed sills taking into account of morphological effects in low-gradient rivers through clear water laboratory tests. Later, their result was generalized by Lenzi et al. (2002) to cover steep channels. Under similar slopes and hydrological settings, an equation developed through laboratory results to predict the maximum scour holes at grade-control structures in alluvial mountain rivers. Lenzi and Comiti (2003) analyzed local scouring downstream of 29 drop structures. Lenzi et al (2003) investigated the main characteristics of local scouring downstream of bed sills in the form of a staircase-like system in high-gradient streams with nonuniform alluvium. They found that the jet regime plays an important role both for the depth and the length of the scour, and consequently affects the scour shape. They proposed two equations for the estimation of the maximum scour depth and length in low and high gradient streams. Marion et al. (2004) conducted a series of tests to determine the effect of bed sill spacing and sediment grading on the potential erosion by jets flowing over the sills. Tregnaghi (2008) conducted some experimental runs in the case of clear water and live bed scouring at bed sills placed in steep gravel bed streams. He concluded that the percentage reduction in maximum scour depth in the case of sediment feeding compared with the clear water tests is considerable. Chinnarasri and Kositgittiwong (2008) conducted some experimental tests in steep slopes and bed sills with different sill spacing. They proposed a simple equation based on nonlinear regression model for relative maximum scour depth at the equilibrium condition.

Although useful in many circumstances, these empirical formulae have one key shortcoming. Specifically, due to wide ranges of hydraulic and sediment characteristics of flow and also bed slopes in rivers, application of any empirical equation doesn't reflect the complex actual conditions of river and structure itself and also the boundary conditions at the downstream of structures. Owing to rapid increase in successful applications of neural computing, machine learning and evolutionary algorithms in many fields of hydraulic engineering, and also owing to high complexity of scouring phenomena at bed sills, there is a need to explore the applicability of these new methods in prediction of maximum scour depth at bed sills. In this regard, Guven and Gunal (2008) using genetic programming (GP) provides alternative formulation for prediction of local scour downstream of grade-control structures. Azamathulla (2012) presents an equation using gene expression programming (GEP) for prediction of scour depth downstream of sills. In this study, using the 226 experimental data set of maximum scour depth at bed sills from literatures in different canal bed slopes and at clear water scouring, applicability of new methods of the GA, GEP, and M5 tree model have been examined in prediction of relative maximum scour depth at bed sills. The results have been compared with the empirical equations obtained by previous researchers.

11.2 Material and Methods

11.2.1 Physical Definition of Scouring

According to Gaudio et al. (2000), the main variable of interest, equilibrium maximum scour depth (y_s), in the case of uniform sediment beds is mainly dependent on flow and sediment characteristics as follows:

$$y_s = f\left(g, \upsilon, \rho_w, \rho_s, q, q_s, h, D, S_0, S_{\mathrm{eq}}, L\right) \tag{11.1}$$

where g = acceleration of gravity, υ = kinematic viscosity of water, ρ_w, and ρ_s = density of water and sediment, respectively, q and q_s = water and sediment discharge per unit width supplied by upstream, respectively, h = water depth of uniform flow condition, D = characteristic grain size, S_0 and S_{eq} = initial and equilibrium bed slopes, respectively, and L = horizontal spacing between sills. This is a general definition of the maximum scour depth for hydraulic, geometric, and sediment properties (see Fig. 11.1).

The application of Buckingham's π-theorem leads to identification of the following dimensionless group (Chinnarasri and Kositgittiwong 2008):

$$\frac{y_s}{H_s} = f_2\left(\frac{a}{H_s}, \frac{a}{\Delta D_{50}}, \frac{L}{H_s}, \frac{D_{50}}{H_s}, S_0\right) \tag{11.2}$$

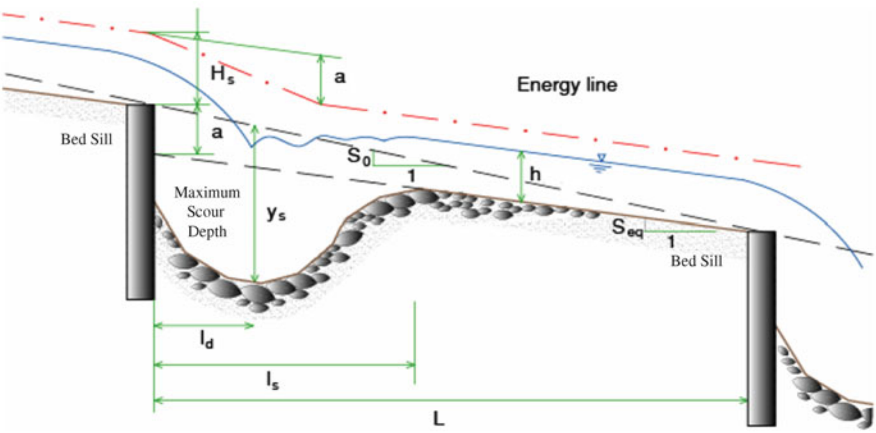

Fig. 11.1 Schematic of scour depth and length downstream of a bed sill (Tregnaghi 2008)

where $\Delta = (\rho_s - \rho_w)/\rho_w$ is the relative submerged density of sediment, $H_s = 1.5\sqrt[3]{q^2/g}$ is critical-specific energy on the sills and a = morphological jump, which was first introduced by Gaudio et al. (2000). This important factor defines a geometrical correspondence between the initial and equilibrium bed slopes and the spacing between sills:

$$a = \left(S_0 - S_{\mathrm{eq}}\right)L \tag{11.3}$$

11.2.2 Scouring Prediction at Bed Sills

11.2.2.1 Empirical Equations

According to non-dimensional parameters obtained for maximum scour depth at bed sills, some empirical equations based on regression analysis of experimental data have been developed. These equations are presented in Table 11.1.

11.2.2.2 Genetic Algorithm

Genetic algorithm (GA) technique is capable of solving complex problems that the traditional algorithms have been unable to conquer. This algorithm begins by creating an initial random set of potential solutions for a particular problem. Then, the fittest "parents" are selected and "children" are generated by means of sexual reproduction (crossover) or asexual alteration (mutation). In crossover, two parents swap random pieces of information with each other while in mutation, a piece of information is replaced by another randomly generated piece. Finally, the resulting solutions (children) are evaluated for their fitness (effectiveness) and selected for reproduction. This process is repeated over-successive generations until a stopping criterion is met (Sharifi 2009).

Once the initial population is generated, each chromosome is evaluated and its "goodness" (fitness) is measured using some measure of fitness function. Then, based on the value of this fitness function, a set of chromosomes is selected for breeding.

Table 11.1 Empirical equations for maximum scour depth prediction

Empirical equation	Investigator	Eq. Number
$\frac{y_s}{H_s} = 1.45\left(\frac{a}{H_s}\right)^{0.86} + 0.06\left(\frac{a}{\Delta d_{50}}\right)^{1.49} + 0.44$	Lenzi et al. (2004)	(11.4)
$\frac{y_s}{H_s} = 1.6\left(\frac{a}{H_s}\right)^{0.61} + 1.89\left(\frac{a}{\Delta d_{50}}\right)^{0.21} - 2.03$	Chinnarasri and Kositgittiwong (2008)	(11.5)
$\frac{y_s}{H_s} = 3\left(\frac{a}{H_s}\right)^{0.6} SI^{-0.19}\left(1 - \mathrm{e}^{-0.25\frac{L}{H_s}}\right)$	Tregnaghi (2008)	(11.6)

In order to simulate a new generation, genetic operators such as crossover and mutation are applied to the selected parents. The offsprings are evaluated and the members of the next generation population are selected from the set of parents and offsprings. This cycle continues until the termination criterion is met (Sharifi 2009).

In this study, the absolute percentage error of output parameter prediction was selected as the performance measure. The selected objective function is as follows:

$$f = \mathrm{Min} \sum_{i=1}^{i=N} \left(\left(\frac{y_s}{H_s} \right)_{\mathrm{exp}} - \left(\frac{y_s}{H_s} \right)_{\mathrm{cal}} \right)^2 \tag{11.7}$$

where N is the number of sample tests and the subscripts exp and cal refer to experimental value and the predictions obtained using each model selected in this study, respectively.

11.2.2.3 Gene Expression Programming

GEP, which is an extension of the GP (Koza 1992), is a search technique that evolves computer programs of different sizes and shapes encoded in linear chromosomes of fixed lengths. The chromosomes are composed of multiple genes, each gene encoding a smaller subprogram. Furthermore, the structural and functional organization of the linear chromosomes allows the unconstrained operation of important genetic operators such as mutation, transposition, and recombination (Azamathulla 2012).

11.2.2.4 M5 Tree Model

Dividing a complex modeling problem into a number of subproblems and combining their solutions is the main idea in building model trees (MT). In this idea, the parameter space is split into areas (subspaces) and a linear regression model is built in each of them, which is an “expert” for that subspace. The algorithm makes it possible to split the multidimensional parameter space into subspaces and to generate the models automatically for each subspace according to an overall quality criterion. First, the initial tree is built and then the initial tree is pruned (reduced) to overcome the over-fitting problem (that is a problem when a model is very accurate on the training data set and fails on the test set). Finally, the smoothing process is employed to compensate for the sharp discontinuities between adjacent linear models at the leaves of the pruned tree (this operation is not needed in building the decision tree). In smoothing, the adjacent linear equations are updated in such a way that the predicted outputs for the neighboring input vectors corresponding to the different equations are becoming close in value (Witten and Frank 2005).

Table 11.2 Range of geometric and hydraulic parameters for scouring at bed sills

Symbol	variable definition	Variable range	Mean value
L (m)	Sills spacing	0.4–2.5	1.07
S_0	Initial bed slope	0.0059–0.268	0.1099
Q (L/s)	Flow discharge	0.68–30.6	16.5
D_{50} (mm)	Sediment mean diameter	0.6–9.0	6.17
y_s (cm)	Maximum scour depth	2.4–29.8	14.45

Table 11.3 Range of input and output parameters used in this study

Dimensionless parameter	Maximum value	Minimum value	Mean value
a/H_s	9.703	0.096	2.12
$a/\Delta D_{50}$	164.62	0.494	23.906
L/H_s	55.74	0.1531	17.736
D_{50}/H_s	0.4615	0.0136	0.106
S_0	0.268	0.0059	0.1099
y_s/H_s	10.617	0.261	2.12

11.2.2.5 Data Set

Two hundred and twenty six experimental data of maximum scour depth at bed sills in clear water conditions have been collected and used in this chapter. These data are from Lenzi et al. (2002), Gaudio and Marion (2003), Marion et al (2004), Tregnaghi (2008), and Chinnarasri and Kositgittiwong (2008). Range of variations, as well as the mean values of experimental data, is shown in Table 11.2.

11.2.2.6 Selection of Input and Output Parameters

Based on dimensional analysis, the parameters of a/H_s, $a/\Delta D_{50}$, L/H_s, D_{50}/H_s, and S_0 have been selected as input variables and relative maximum scour depth, y_s/H_s, has been selected as output variable. Table 11.3 reports the ranges of input and output parameters, which are used in this study.

11.2.3 Experimental Setup

In this study, GA_SOLVER tool in Microsoft Excel was adopted for the GA modeling. For the GP modeling, the Gene_XPro_Tools software was used. Finally, for the model tree experiment, a model tree was built using the M5 algorithm implemented in WEKA software (Witten and Frank 2005).

11.3 Results

11.3.1 GA Model

Applying GA_Solver for developing a new equation, following relationship has obtained for training data set:

$$\frac{y_s}{H_s} = 0.00076\left(\frac{a}{H_s}\right)^{16.999}\left(\frac{a}{\Delta D_{50}}\right)^{-16.464}\left(\frac{L}{H_s}\right)^{-0.0613}\left(\frac{D_{50}}{H_s}\right)^{-16.595} S_0^{0.0802} \quad (11.8)$$

Results of using the above equation for training and testing data have been presented in Fig. 11.2. As can be seen, in all over the data ranges, this equation shows good agreement between experimental and predicted values of maximum scour depth at bed sills. Obtained R^2 values of 0.96 and 0.94 for training and testing data, respectively, indicate this agreement.

11.3.2 GEP Model

In this study, according to training data, another equation has been developed using GeneXProTools program as following:

$$\frac{y_s}{H_s} = \ln\left(\frac{a}{\Delta D_{50}} + \frac{a}{H_s} + 9.8561\frac{D_{50}}{H_s}\right) + \frac{D_{50}}{H_s}\left(\frac{a}{\Delta D_{50}} - \frac{S_0}{D_{50}/H_s}\right) + \frac{D_{50}/H_s}{\log(a/H_s) - (a/(\Delta D_{50}))^{1/3}} \quad (11.9)$$

This equation with $R^2 = 0.97$ has considerable accuracy. By using this equation for testing data, R^2 is obtained as 0.97. These results have been shown in Fig. 11.3. The detailed information of the GEP model is indicated in Table 11.4.

11.3.3 M5 Tree Equations

For training data, seven linear models have been derived based on mainly variations of bed slope. This bed slope dividing is very important from hydraulic and morphologic point of view which defines two different conditions for bed sill scouring. These linear models, as well as the classification criteria, are as follows:

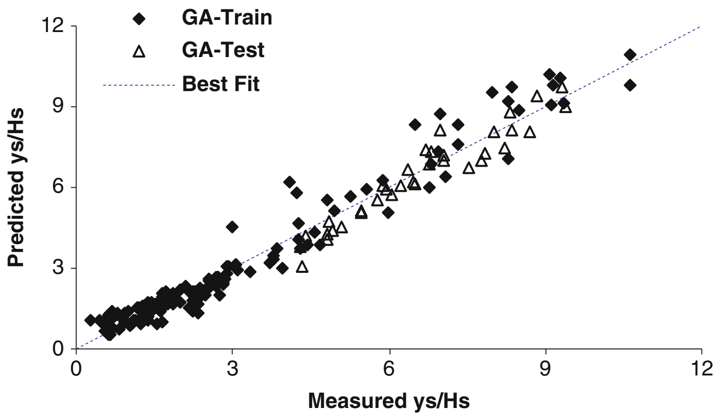

Fig. 11.2 Proposed GA model for relative maximum scour depth prediction

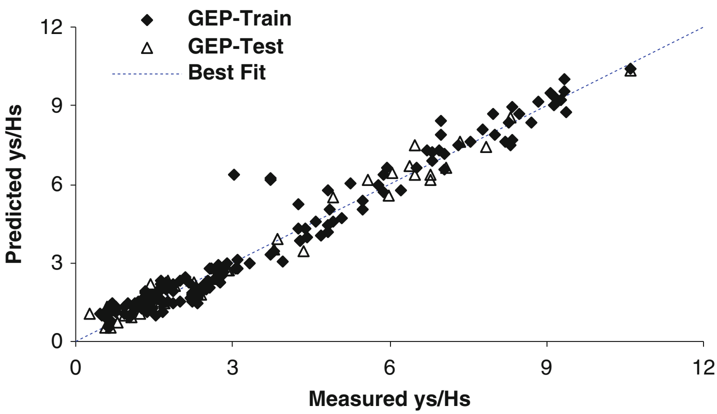

Fig. 11.3 GEP model results of relative maximum scour depth for training and testing data in this study

Table 11.4 Parameters of the optimized GEP model

Parameter	Description of parameter	Parameter amount
P1	Chromosomes	30
P2	Genes	3
P3	Mutation rate	0.044
P4	Inversion rate	0.1
P5	Function set	×, power
P6	One-point recombination rate	0.3
P7	Two-point recombination rate	0.3
P8	Gene recombination rate	0.1
P9	Gene transposition rate	0.1
P10	Linking function	Subtraction

$S_0 <= 0.162$:
| $a/H_s <= 0.579$:
| | $a/H_s <= 0.385$: LM1(37/14.364%)
| | $a/H_s > 0.385$: LM2(28/16.214%)
| $a/H_s > 0.579$:
| | $a/(\Delta d_{50}) <= 4.266$: LM3(17/14.957%)
| | $a/(\Delta d_{50}) > 4.266$: LM4(28/8.399%)
$S_0 > 0.162$:
| $a/H_s <= 3.744$: LM5(25/35.412%)
| $a/H_s > 3.744$:
| | $a/H_s <= 6.218$: LM6(20/53.031%)
| | $a/H_s > 6.218$: LM7(20/62.068%)

LM num 1

$$\frac{y_s}{H_s} = 0.812\left(\frac{a}{H_s}\right) + 0.0285\left(\frac{a}{\Delta d_{50}}\right) + 0.5264S_0 + 0.8136 \tag{11.10}$$

LM num 2

$$\frac{y_s}{H_s} = 0.9265\left(\frac{a}{H_s}\right) + 0.0285\left(\frac{a}{\Delta d_{50}}\right) + 0.5264S_0 + 1.0991 \tag{11.11}$$

LM num 3

$$\frac{y_s}{H_s} = 0.3236\left(\frac{a}{H_s}\right) + 0.1019\left(\frac{a}{\Delta d_{50}}\right) + 0.5264S_0 + 1.4 \tag{11.12}$$

LM num 4

$$\frac{y_s}{H_s} = 0.3263\left(\frac{a}{H_s}\right) + 0.0854\left(\frac{a}{\Delta d_{50}}\right) + 0.5264S_0 + 1.7508 \tag{11.13}$$

LM num 5

$$\frac{y_s}{H_s} = 0.351\left(\frac{a}{H_s}\right) + 0.0029\left(\frac{a}{\Delta d_{50}}\right) + 0.8224S_0 + 3.2061 \tag{11.14}$$

LM num 6

$$\frac{y_s}{H_s} = 0.4555\left(\frac{a}{H_s}\right) + 0.0029\left(\frac{a}{\Delta d_{50}}\right) + 0.8224S_0 + 3.7096 \tag{11.15}$$

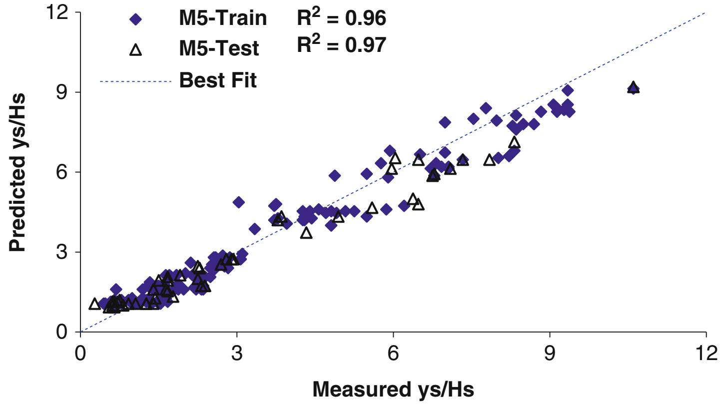

Fig. 11.4 Proposed M5 model relative maximum scour depth obtained for training and testing data

LM num 7

$$\frac{y_s}{H_s} = 0.4544\left(\frac{a}{H_s}\right) + 0.0029\left(\frac{a}{\Delta d_{50}}\right) + 0.8224S_0 + 4.3617 \tag{11.16}$$

Calculation results for training and testing data have been presented in Fig. 11.4. According to R^2 values, good accuracy has been obtained in comparison to experimental maximum relative depth scours.

In Fig. 11.5, all results including selected models, as well as empirical equations, are shown for data set of this study. As can be seen, the overall trend of Eq. 11.4 (Lenzi et al. 2004) is overestimation of maximum scour depth with very large errors especially at high relative scour depths. Also, it is interesting to note that Eq. 11.5 (Chinnarasri and Kositgittiwong 2008) has good agreement with measured data. Owing to simplicity of this equation and more importantly, its dependency to only two dimensionless parameters, it can be proposed as an option for engineers to predict maximum scour depth at bed sills with sufficient accuracy ($R^2 = 0.91$). Equation 11.6 (Tregnaghi 2008) underestimates the scour depth with high errors, especially at low relative scour depths. All selected models in this study (GA, GEP, and M5) have high accuracy through all ranges of experimental data.

11.4 Performance Analysis of Results

To validate the results for the training and testing sets, several common statistical measures are used, such as R^2 (coefficient of determination), RMSE (root mean square error), and AE (the average error) (Azamathulla 2012).

The results of statistical analysis are presented in Table 11.5. Based on this table, it is indicated that among different models considered in this study, Eq. 11.4

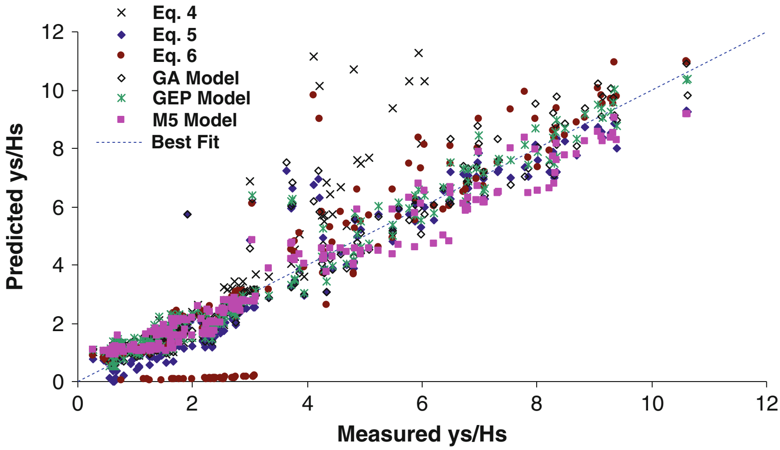

Fig. 11.5 Comparison of all empirical equations and selected models results for prediction of relative maximum scour depth

Table 11.5 Evaluation of empirical equations and selected models for scour depth prediction

	Training			Testing			All data		
Method	R^2	RMSE	%AE	R^2	RMSE	%AE	R^2	RMSE	%AE
Empirical Eqs.									
Eq. 11.4	–	–	–	–	–	–	0.61	26.06	−161
Eq. 11.5	–	–	–	–	–	–	0.91	0.774	5.41
Eq. 11.6	–	–	–	–	–	–	0.82	1.291	4.7
GA model	0.96	0.442	−0.93	0.94	0.938	−1.24	0.95	0.805	−0.98
GEP model	0.97	0.451	−8.46	0.95	0.555	−11.3	0.96	0.535	−8.94
M5 model	0.97	0.537	−4.84	0.96	0.652	−6.68	0.96	0.561	−5.17

(Lenzi et al. 2004) has the worst accuracy and therefore, is not recommended for application. On the other hand, the GA, GEP, M5, and even simple empirical equation of Chinnarasri and Kositgittiwong (11.5) have the best accuracies. By consideration of all statistical parameters, it seems that the GA model can be proposed as an option for prediction of maximum scour depth at bed sills. In addition, the Chinnarasri and Kositgittiwong (2008) equation, with requiring for only two input parameters and also having good accuracy, may be considered as a suitable approach.

11.5 Conclusions

Soft computing tools such as the GA, GEP, and M5 tree approaches were used to derive new expressions for the prediction of scour downstream of bed sills. The proposed GA equation is found to be useful to estimate scour depth for mountain rivers for various bed slopes. Performance of the GA expression is carried out by comparing its predictions with the published data ($R^2 = 0.96$ and RMSE $= 0.442$). The comparison shows that the new expression has the least RMSE and the highest coefficient of determination. The expression is found to be particularly suitable for bed slopes where predictions are very close to the measured scour depth. These models can be further extended for the estimation of scour geometry based on additional prototype data of parameters such as type of rock bed classified as per rock quality designation (RQD) and rock mass rating (RMR).

References

Azamathulla HM (2012) Gene expression programming for prediction of scour depth downstream of sills. J Hydrol 460–461:156–159

Bormann N, Julien PY (1991) Scour downstream of grade-control structures. J Hydraul Eng ASCE 117(5):579–594

Chinnarasri C, Kositgittiwong D (2008) Laboratory study of maximum scour depth downstream of sills. ICE Water Manage 161(5):267–275

Gaudio R, Marion A (2003) Time evolution of scouring downstream of bed sills. J Hydraul Res IAHR 41(3):271–284

Gaudio R, Marion A, Bovolin V (2000) Morphological effects of bed sills in degrading rivers. J Hydraul Res IAHR 38(2):89–96

Guven A, Gunal M (2008) Genetic programming approach for prediction of local scour downstream of hydraulic structures. J Irrig Drain Eng ASCE 134(2):241–249

Koza JR (1992) Genetic programming: on the programming of computers by means of natural selection. MIT Press, Cambridge, MA

Lenzi MA, Comiti F (2003) Local scouring and morphological adjustments in steep channels with check-dams sequences. Geomorphology 55:97–109

Lenzi MA, Marion A, Comiti F, Gaudio R (2002) Local scouring in low and high gradient streams at bed sills. J Hydraul Res IAHR 40(6):731–739

Lenzi MA, Marion A, Comiti F (2003) Interference processes on scouring at bed sills. Earth Surf Process Landf 28(1):99–110

Lenzi MA, Comiti F, Marion A (2004) Local scouring at bed sills in a mountain river: Plima river, Italian alps. J Hydraul Eng ASCE 130(3):267–269

Marion A, Lenzi MA, Comiti F (2004) Effect of sill spacing and sediment size grading on scouring at grade-control structures. Earth Surf Process Landf 29(8):983–993

Sharifi S (2009) Application of evolutionary computation to open channel flow modeling. PhD Thesis in Civil Engineering, University of Birmingham, p 330

Tregnaghi M (2008) Local scouring at bed sills under steady and unsteady conditions. PhD Thesis, University of Padova, p 161

Witten IH, Frank E (2005) Data mining: practical machine learning tools and techniques with Java implementations. Morgan Kaufmann, San Francisco