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Using Genetic Programming to Predict Scour Downstream Rapid Hydraulic Structures from Experimental Results

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ABSTRACT: Rapid hydraulic structures are used in Poland Stream Mountains excessively to regulate flow by changing its slope at certain locations while allowing for fish passage. Local scour downstream the rapid is an important issue regarding its safety. This paper presents experimental investigation for scour holes downstream a rapid structure using a small scale physical model. Results are used with other data presented in literature for similar structures to develop an equation for the prediction of maximum scour hole downstream rapids. For this purpose Genetic Programming (GP) is utilized as a tool for developing the required relation. It is shown that GP could produce formulae relating scour hole depth and various rapid parameters with less error than some of available regression equations.

Keywords: Rapid hydraulic structures, low head structures, scour, Genetic Programming

1 INTRODUCTION

There is very often a necessity to regulate a river or a stream by changing its slope (what is called: river training works), especially in mountain regions where streams are characterized by high gradients and heavy scouring and erosion tend to occur. In such cases designing and constructing of hydraulic structures has been advised for stabilizing a riverbed and riverbanks (Rhone 1977, Ratomski, 1992). Usually such structures are drop hydraulic structures. Their construction is well known to designers and they are described in detail in the professional literature (e.g. Shields and Cooper 1995, Rosgen 2001, Scurlock and Thornton 2011 and 2012). Unfortunately in many places, if a structure is built, it can spoil the natural beauty of a mountain stream. If it functions properly in terms of hydraulics, it is rarely similar to the natural geomorphological features of a stream (Ratomski, 1992). Construction of rapid hydraulics structures (RHS) similar to natural river riffles is advised when considering a channel slope reduction (Kajak, 1992, Ślizowski, 1993). Such hydraulic structures are environmentally friendly, since they simulate a natural river bed and river bed forms (riffles), do not require additional fish passage consideration, and aerate flowing water naturally (Bhuiyan and Wormleaton 2007, Novak et al. 1996). Above all they are similar to natural river features and do not disturb a river cross-section appearance when well-constructed (see Figure 1).

The process of creating local scour resulting from water and debris is one of the least to identified problems in the rapid hydraulic structure systems. So far, there is no sufficiently precise mathematical description of the process of local erosion arising downstream the rapid structure. Developing fully reliable predictions on the basis of laboratory tests has often been impossible because of the time required to obtain experience the so-called final scour. However, Mason and Arumugan (1985) provided comprehensive data analysis in available literature to demonstrate the validity of the ultimate scour hole concept. Lack of understanding of the process of creating local scour below the rapid structure is the main reason for failure of structure in various studies (e.g. Bormann and Julien 1991). Scour downstream similar structures (e.g. block ramps and grade-control structures) has been carried out by various researchers. Veronese (1937) conducted one of the first studies on scour downstream hydraulic structure. The characteristic parameters defining scour hole downstream hydraulic structure have been experimentally studied by Hassan and Narayanan (1985) and Farhoudi and Smith (1985). Bormann and Julien (1991) used a large scale experiment to investigate the scour downstream a grade control structure with a unit discharge of 2.5m^2/s. Mossa (1998) and D'Agostino and Ferro (2003) analyzed the scour formation downstream grade control structures. Lenzi and Comiti (2003) analyzed scour hole formation downstream 29 drop structures, Marion et al. (2004) experimentally analyzed the effect of bed sill spacing and sediment grading on potential erosion by jets over fills. Ben Meftah and Mossa (2006) analyzed the formation of scour holes downstream bed sills in low gradient channels. Pagliara and Hager (2004) conducted experimental work to study the scour process and characteristics downstream a block ramp in case of uniform bed material. More recently, Pagliara (2007),and Pagliara and Palermo (2008) investigated the scour mechanics downstream a block ramp and examined the influence of sediment gradation on the scour mechanism using two physical models. Scurlock and Thornton (2012) studied the equilibrium scour formation downstream three dimensional grade control structures.

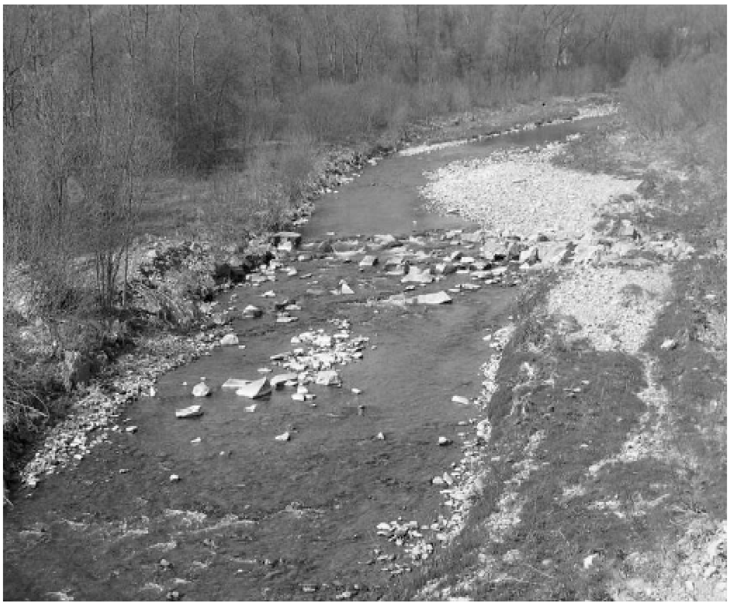

Figure 1. RHS on the Krzczonowski stream (photo by A. Radecki-Pawlik)

Most of the previous experimental studies aimed at characterizing the scour hole downstream grade control structure by a maximum scour depth, which is a function of the incoming flow conditions and soil parameters representative of bed particle size distribution (e.g. Mason and Arumugam 1985, Bormann and Julien 1991, Lenzi and Comiti 2003, Marion et al. 2004 and Pagliara 2007). However, there are no reliable equations for calculating scour downstream rapid hydraulic structures and thus it is of usual practice to adopt scour formulae developed for other structures under different hydraulic conditions. While these formulae provide estimates for the required scour depth, they might have some deficiencies in capturing accurately the scour downstream rapid hydraulic structures. Errors in prediction of scour hole using some of these formulae can reach 300%. Thus, it is required to have specific equations developed mainly for rapid hydraulic structures considering real measured rapid parameters.

Recently, evolutionary algorithms have been used as a superior alternative for regression analysis and artificial neural networks, for finding relations between various parameters and producing a higher R-squared value and less mean error in prediction using newly developed equation. Genetic programming (GP) is known as a technique with the capability of generating mathematical equations, which are able to define models for the given training data. Genetic programming was proposed by Koza (1992). GP is founded on the basic principle of Darwin's theory of evolution in nature. GP attempts and succeeds at applying the evolutionary theory in order to find the best or the most appropriate equation (solution)for a problem. The motivation of using a GP approach is its ability to evolve a model based entirely on prior data without the need of making underlying assumptions.

Applications of evolutionary algorithms, especially genetic programming (GP) in water and environmental engineering is not as much as the other soft computing tools of artificial neural networks. They are restricted to relatively fewer sub-areas including; rainfall-runoff relationship and unit hydrographs in catchments (Aytek and Alp 2008, Wigham and Crapper 2001, Savic et al. 1999, Keijer and Babovic 2002, Dorado et al. 2003, and Rabunal et al. 2006), sewer and water supply networks (Dorado et al. 2002, Babovic et al. 2002), river flow and water quality in watersheds (Drunpob et al. 2005, Harris et al. 2003, Giustolisi 2004, Preis and Otsfeld 2008), oceanic and sea coastal waves (Gaur and Deo 2008, and Ghorbani et al. 2010), irrigation planning (Raju and Kumar (2004), river channel scour downstream spillway

(Azamathulla et al. 2008), pan evaporation and evapotranspiration (Guven & Guani 2008, and Shiri and Kisi 2011), and suspended sediment transport in open channel (Ayetk and Kisi 2008). Guven & Guani (2008) utilized the gene expression programming approach for prediction of local scour downstream sharp crested control grade structure. They provided a complicated equation relating various parameter to maximum scour hole depth.

This paper aims at utilizing the power of the genetic programming to develop relations to predict scour hole depth downstream rapid hydraulic structures as a function of incoming flow conditions, rapid geometric characteristics and soil parameters using experimental data measured by the authors in an experiment to simulate real rapid structures and other published data of similar hydraulic investigations performed by Pagliara (2007). First an overview of the basic theory of genetic programming is given accompanied by implementation technique steps. Afterwards, a description for the experimental setup used to collect scour data is given with the results. Finally, the GP is utilized to develop empirical relationships between various controlling parameters and the maximum scour depth downstream a rapid hydraulic structure. The developed relation is compared to other available relations.

2 EVOLUTIONARY ALGORITHMS

Evolutionary Algorithms (EAs) is a class of solving technique based on the Darwinian theory of evolution which involves the search of a population of solutions and not only one. A possible and acceptable solution i.e. a member of the population is called an individual. Each iteration of an EA involves a competitive selection that weeds out poor solutions through the evaluation of a fitness value that indicate the quality of the individual as a solution to the problem. The evolutionary process involves at each generation a set of genetic operators that are randomly applied on the individuals, typically recombination (or crossover) and mutation.

2.1 *Genetic Programming (GP)*

Genetic programming is an extension to Genetic Algorithms (GA). GA is an optimization and search technique based on the principles of genetics and natural selection. A GA allows a population composed of many individuals (chromosome) to evolve under specified selection rules to a state that maximizes the "fitness" (i.e. minimizes the cost function). The GP is similar to genetic algorithms but unlike the latter its solution is a computer program or an equation as against a set of numbers in the GA.

In GP, a random population of individuals (equations or computer programs) is created, the fitness of individuals is evaluated and then the 'parents' are selected out of these individuals. The parents are then made to yield 'offspring's' by following the process of reproduction, mutation and crossover. The creation of offspring's continues iteratively until a specified number of offspring's in a generation are produced and further until another specified number of generations are created. The resulting offspring at the end of all this process is the solution to the problem. The GP transforms one population of individuals into another one in an iterative manner by following the natural genetic operations like reproduction, mutation and crossover. Each individual contributes with its own genetic information to the building of new offspring adapted to the environment with higher chances of surviving. The solution for the problem provided by the GP algorithm is a tree as seen in Figure 2.

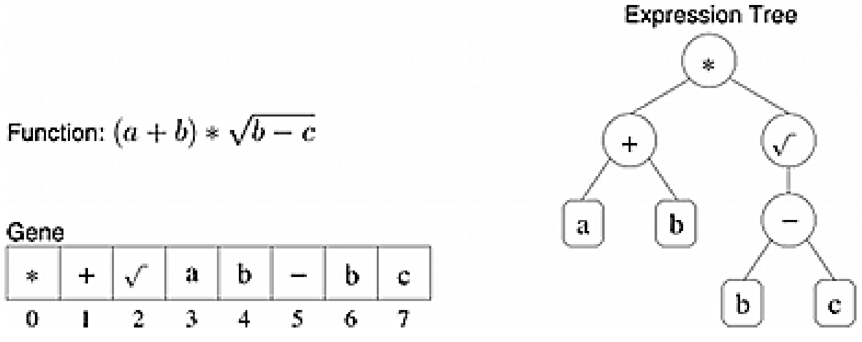

Figure 2. Tree representation for a GP function

A tree is a model representation that contains nodes and leaves. Nodes are mathematical operators (multiplication, subtraction, etc.). Leaves are terminals and trees are manipulated through genetic operators. The crossover operator points a tree branch and exchanges it with another branch and obtains new trees. The mutation operator changes the branch for a random new branch. Reproduction means exact duplication of the program if it is found to be accepted by the fitness criteria (Figure 3). Fitness functions are employed to select various individuals for crossover, mutation, reproduction and to determine how good the individuals are at solving the given problem. The fitness function assesses how an individual is fitted to the environment of a domain problem, after calculating the fitness for all individuals. Many varieties of fitness function can be applied for evaluating performance of generated computer program. GP evolves computer programs to solve problems by executing the following steps using GPLAB Code (El-Sayed 2011);

Step1: One or more initial population of individuals is randomly generated with functions and terminals related to the problem domain.

Step2: The implementation of GP iteratively performs the following steps until the termination criterion has been satisfied

i. The fitness value of every individual is estimated according to a selected fitness measure
ii. All individuals in the population are sorted based on their fitness values
iii. The next generation is produced using the genetic operations (reproduction, crossover and mutation)
iv. The termination criterion is checked. If it is not satisfied, the next iteration is performed if satisfied go to step 3.

Step3: The result may be a solution to the problem domain.

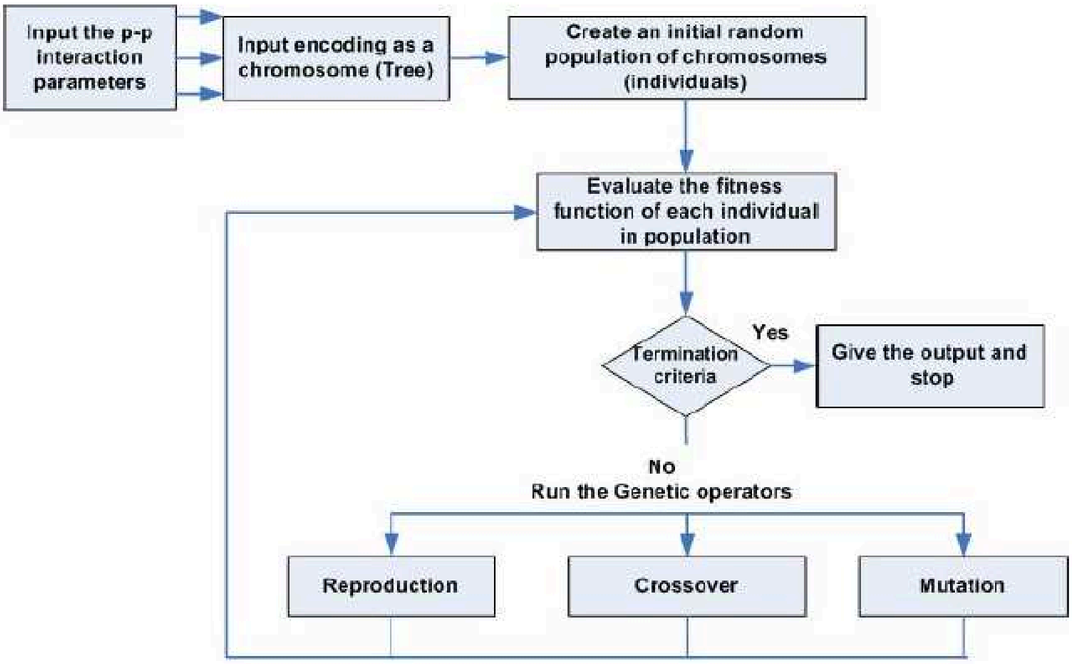

Figure 3. Genetic programming flow chart

3 EXPERIMENTAL SETUP

The experiment was carried out in the laboratory flume at the Department of Hydraulics Engineering and Geotechnic, Agricultural University of Cracow (see Figure 6).The banks and a bed of the model were stable and wash-resistant. The model has and upstream water tank with calibrated notch weir, at the downstream of the weir a water-wave calming device (honeycomb) is installed. In the middle of the channel, the rapid structure module is installed and mobile bed material is placed all over the flume bed. Measurement devices include; velocitimeters, pin-gauges, and calibrated notches

The study adopted the simplest design solution rapids on the crown straight sill height of 0.06 m drop across the same longitudinal length. Known from the literature are other smart structures, such as perfecta curved crown rapids; alternating elongated drop, and a curved cross section, but these structures are recommended for larger widths of the troughs. Because it was assumed that the study will only affect mountain streams generally characterized by a small width, the ratio B / h < 4.5 is recommended for such streams and respected in the current study. Aim of the study carried out by analyzing six models of rapid structure design with increased roughness (2A - 8A).

Model rapids of natural stone are made in 1:10 scale in the riverbed hydraulic dimensions: length 25.00 m, width 0.60 m, depth 0.80 m (Fig. 4 shows a schematic of the rapid experiment). Section of the canal above and below the rapids was made of concrete sand bed as armoring layer. Only a section of the channel immediately below the rapids on the length of 4.50 m made as to observe the resulting scour hole. The channel was filled with sediment of characteristic diameter d_{90} = 0.003 m

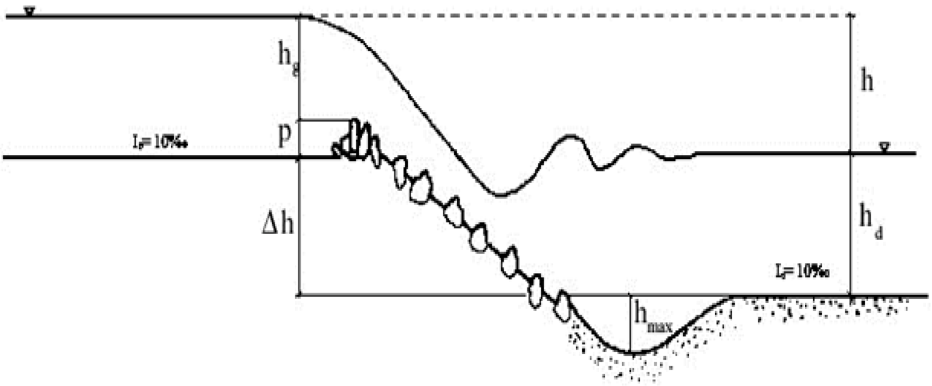

Figure 4. Sketch of the rapid structure with artificial roughness

In order to increase roughness and bring it to the roughness in a mountain stream, the bottom was lined with fine grit stone that protruded above the bottom line of about = 0.01 m Model rapids were made as part of removable concrete slab with inserted natural stones protruding more than the bottom line of rapids with 0.045 m stones arranged in a checkerboard pattern in the front row of 0.05 m, the distance between rows 0.075 m to backpressure water table position at the inlet of the upper rapids made the threshold with a height of 0.06 m . Experiments were carried out for a rapid drop slopes of 1:4.5, 1:6, 1:10 and height 0.10 and 0.30 m and for flow rates ranging 0.0245m^3/s, 0.0490m^3/s, and 0.0735m^3/s. Figure 6 shows the contour plot of scour downstream the rapid structure under the flow of 0.0735m^3/s. Experimental measurements are presented in Table 1.

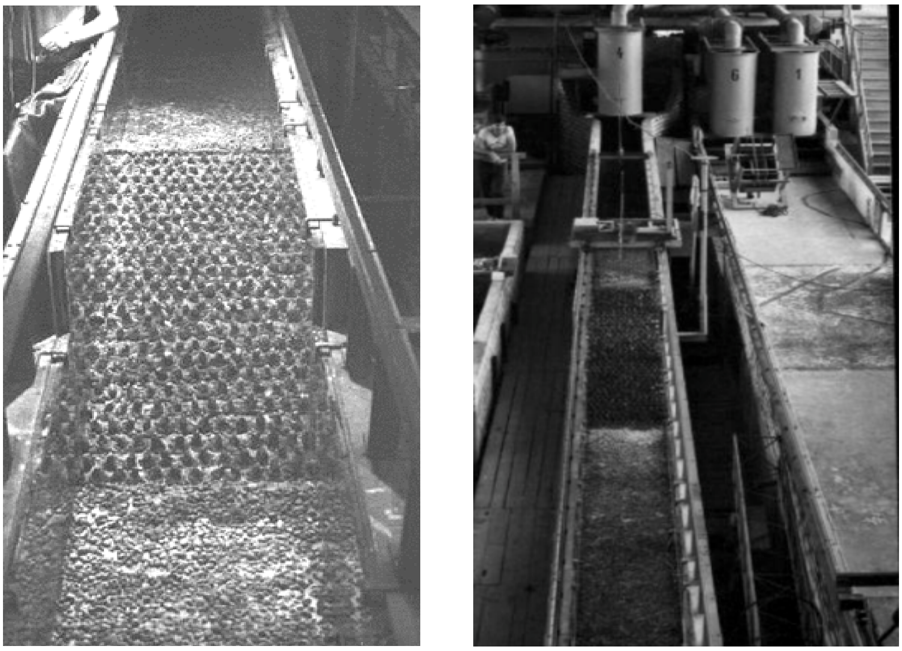

Figure 5. Model of rapid structure in laboratory flume

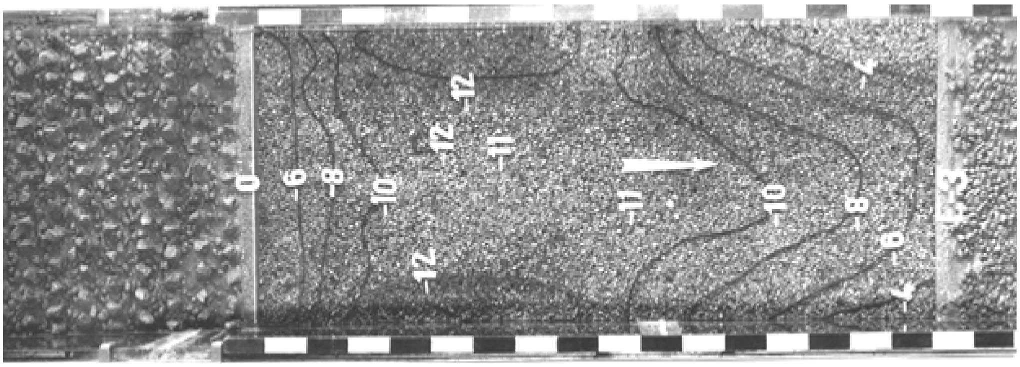

Figure 6. Contour plot of scour below rapid 3A: Q = 0.0735 m^3/s, s = 1:6, h = 0.10 m

Table 1. Scour depth from model studies according to rapid parameters

Rapid	Rapid discharge Q (m^3/s)	Rapid velocity v (m/s)	Height difference h (m)	Rapid slope, s	Scour depth h_{max} (m)
2A	0,0245	1.20	0.1424	0.22	0.07
	0,0490	1.445	0.1442	0.22	0.12
	0,0730	1.710	0.1441	0.22	0.15
3A	0,0245	1.100	0.1434	0.167	0.08
	0,0490	1.630	0.1454	0.167	0.10
	0,0730	1.945	0.1454	0.167	0.14
4A	0,0245	1.220	0.1481	0.10	0.08
	0,0490	1.750	0.1525	0.10	0.10
	0,0730	1.805	0.1524	0.10	0.12
6A	0,0245	1.290	0.3485	0.22	0.06
	0,0490	2.190	0.3454	0.22	0.13
	0,0730	2.440	0.3463	0.22	0.18
7A	0,0245	1.160	0.353	0.167	0.06
	0,0490	1.650	0.3551	0.167	0.13
	0,0730	2.050	0.3531	0.167	0.17
8A	0,0245	1.100	0.3654	0.10	0.06
	0,0490	1.480	0.3695	0.10	0.12
	0,0730	1.880	0.3703	0.10	0.12

These experiments are similar to those performed by Pagliara (2007) and Bormann and Julien (1991). Pagliara (2007) performed experimental investigations on block ramps to determine the impact of bed material gradation on the formation of the scour hole downstream the structure under various flow conditions. On the other hand, Bormann and Julien (1991) performed experimental investigation on large scale flume to determine the scour hole characteristics downstream a sloping ramp. Both studies provide additional important information with respect to having various rapid slopes, rapid discharges, various sizes and gradation for bed material and large scale rapid very similar to that of mountain streams. Table 2 shows the range of various rapid related parameters as measured in current study and obtained from Pagliara (2007) and Bormann and Julien (1991).

Table 2. Range of various parameters controlling the scour holes considered

Study	Rapid discharge Q (m3/s)	Sediment size d_{90} (m)	Rapid slope, s	Scour depth h_{max} (m)	Coff. of uniformity ($\sigma = \sqrt{d_{84}/d_{16}}$)
Current study	0.02 to 0.07	0.003	0.10 to 0.22	0.06 to 0.18	1
Pagliara (2007)	0.00148 to 0.073	0.016 to 0.0097	0.083 to 0.25	0.0056 to 0.18	1.2 to 2.8
Bormann & Julien (1991)	0.26 to 2.25	0.00158 to 0.00171	0.33 to 1.00	0.10 to 1.52	1
Overall	0.00148 to 2.25	0.00158 to 0.016	0.083 to 1.00	0.0056 to 1.52	1 to 2.8

4 GP MODELS FOR SCOUR PREDICTION

Pagliara (2007) stated that the scour-hole characteristics are related to the ramp slope, water flow discharge, and to the granulometric characteristics of the stream bed material represented as d_{90}. Thus; the maximum scour depth can be written as;

$$h_{max} = f(Q, s, d_{90}, \sigma) \qquad (1)$$

Pagliara (2007) introduced a dimensionless parameter Z_{max}, defined as the ratio of the measured maximum cross sectional scour depth and the approaching flow depth at the ramp, h_1 such that;

$$Z_{max} = f\left(F_{d_{90}}, s, \sigma\right) \qquad (2)$$

where $F_{d_{90}}$ is the densimetric Froude number, $F_{d_{90}} = \sqrt{v_1/g'\,d_{90}}$, v_1 = average approaching flow velocity, d_{90} = channel bed sediment diameter, $g' = [(\rho_s - \rho)/\rho]g$, and ρ_s = channel bed sediment density. Both of these two relations shall be used to develop a GP-based model for prediction of maximum scour hole depth. Data included 18 points from this study, 49 points from Pagliara (2007) and 45 points from Bormann and Julien (1991) with a total of 112points. 80% shall be used for training the model (89 points) and 20% shall be used for testing (23 points).

To apply the GP, we need to define the learning environment using a fitness function. The fitness function defined here is the mean squared error (MSE); it helps an efficient evolution for the model and allows it to travel fitness landscape until it finds an optimal solution for the given problem. The mean square error E_i of an individual program i is defined by the following equation;

$$E_i = \sqrt{\frac{\sum_{j=1}^{n}\left(P_{(ij)} - T_j\right)^2}{\sum_{j=1}^{n}\left(T_j - \bar{T}\right)^2}} \qquad (3)$$

where $P_{(ij)}$ is the value predicted by the program i for fitness case j; T_j is the target value for fitness case j; and $\bar{T} = 1/n \sum_{j=1}^{n} T_j$. For a perfect fit E_i=0, and thus the index of RRSE ranges from 0 to infinity, with zero corresponding to the ideal. Thus the fitness of an individual model f_i can be calculated from the following equation which ranges from 0 to 1000, with 1000 corresponding to perfect fit; $f_i = 1000 \times 1/(1 + E_i)$. It is important to choose the set of functions that will create the chromosomes. These functions are the essence of evolution of the GP; they allow modifications without restrictions leading to compact correct programs for a specific function. The choice of an appropriate function set is not the same for every problem and depends mainly on the program performance with some chosen arguments. If the evolution is not satisfactory, one can use a wider set of functions until optimum fitness is achieved. However, a professional approach would be to initially use the basic mathematical operators (+, -, *, /) to allow for production of simple models. A second run of GP is performed using a different set of functions as shown in Table 3. Then, we have to set the linking function, which is the interaction between all sub-expression trees of the model, these linking functions can be addition, subtraction, division, and multiplication. The choice of linking functions depends on the complexity of the problem and the experience of the model user and for simpler models for a certain problem, addition or subtraction would be appropriate. The last step is to set the values controlling various genetic operations controlling the evolutionary process of GP. The most efficient operator in GP are the mutation and cross over rates; which causes populations of individuals to adapt very efficiently, allowing for the evolution of good solutions to all problems. Values assigned for all genetic operators are shown in Table 3 for various GP models. To test the performance of the developed model, the mean square error MSE, mean absolute error MAE, and relative squared error RSE were used as indicators, as calculated from the following equations respectively;

$$MSE_i = 1/n \sum_{j=1}^{n}\left(P_{(ij)} - T_j\right)^2 \qquad (4)$$

$$MAE_i = \frac{1}{n}\sum_{j=1}^{n}\left|\frac{P_{(ij)} - T_j}{T_j}\right| \qquad (5)$$

$$RSE_i = \frac{\sum_{j=1}^{n}\left(P_{(ij)} - T_j\right)^2}{\sum_{j=1}^{n}\left(T_j - \bar{T}\right)^2} \qquad (6)$$

Table 3. Optimal Parameter settings for the GP Algorithms

Parameters	Settings-GPI-h_{max}
Number of generations	100
Number of populations	500
Function set	+ , - , *, /
Terminal set	Q, s, d_{90}, σ
Fitness function error type	MSE
Selection method	Tournament
Mutation rate	0.01
Crossover rate	0.9

Based on the optimal parameter settings in above table, the following GP-based equations were developed and are considered to be valid within the ranges given back in Table 2. The best individual for all generations for GPI-h_{max} can be presented as;

$$h_{max} = 0.38Qs - Q + \frac{d_{90}}{0.50-Q} + (1.92-\sigma)(d_{90}+Q) \qquad (7)$$

Using the performance indicators discussed before, MSE, MAE, RSE and R-squared, Table 4 shows the comparison between developed GP-model and similar equations (Veronese, Martin, Mason, and Pagliara) for prediction of scour holes downstream ramp structures.

Table 4. Performance of developed equations for h_{max} versus some available equations

	GPI		Veronese	Martin	Mason	Pagliara (2007)
	train	test				
R-Square	0.88	0.84	NA	NA	NA	NA
MSE	0.0259	0.029	0.69	0.55	3.3	NA
MAE	0.087	0.110	0.90	0.99	0.75	33.3
RSE	0.116	0.255	27.1	13.9	60.99	NA

It is noticed that the developed GP relation had the highest representation of scour database, which resulted in highest value of R-squared and lowest values for errors. All existing formulae deviated in their predictions from measurements with huge RSE reaching 60.99 for Mason and 27.1 for Veronese. Due to huge errors in predictions of many of the existing formulae, the R-squared could not be calculated meaning that they do not represent measured data of rapid structures at all. This is mainly attributed to the presence of large scale experimental data, which are outside the limits of values used in developing most of these equations. Thus, this shows the importance of including the measured data from large scale experimental tests that are similar to real rapids on mountain streams. Results show also that genetic programming (GP) is capable of mapping data into a high dimensional feature space with variety of methods to find relations and trends in data. The following figures show the predictions of h_{max} as calculated by the developed GP model versus measured values for both training and testing datasets.

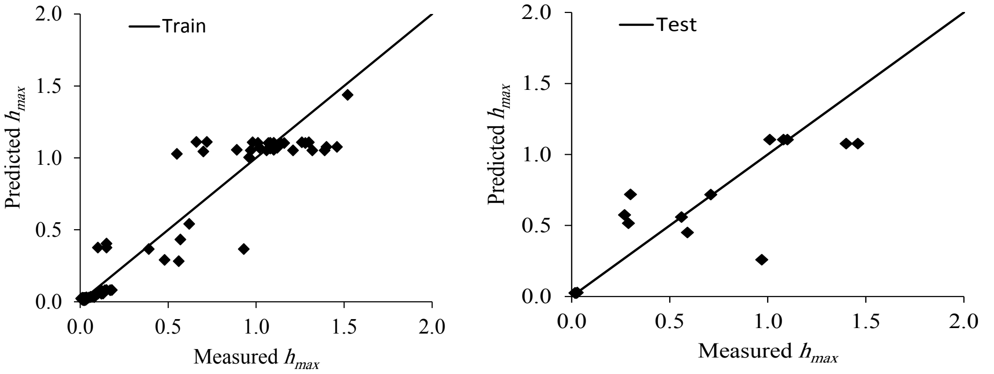

Figure 7. R^2 for training and testing data sets for GPI model for h_{max}

For risk assessment studies, the uncertainties of many influencing parameters have to be included. Thus; Wahl (2004) provided quantitative assessments for the uncertainty in breach parameter prediction using many of the available prediction relations on 108 documented dam failure case studies. In this part of the study, Wahl (2004) approach is adopted to test the ability of the developed GP models to predict scour hole depth. The analysis is applied to the dataset of 112 scour hole measurements including the measurements on large scale experiments. While this could provide some advantages for the GP model, it provides fair indication for comparison of ability of prediction for various equations (Wahl 2004). The uncertainty analysis defines the error in as; $e_{ij} = P_{ij} - T_j$, and then calculates main indicators defined as; mean prediction error ($\bar{e} = \sum_{j=1}^{n} e_{ij}$), width of uncertainty band, $B_{ub} = \pm 2S_e$ and the confidence band around the predicted value $\{\bar{e} + 2S_e, \bar{e} - 2S_e\}$, where S_e is the standard deviation of prediction errors. It is shown that the mean prediction error of developed GP model is -0.192 with prediction error standard deviation of 0.336 and width of uncertainty band of ± 0.67, while the prediction error interval ranged from -0.48 to 0.87. Unfortunately, other formulae produced large errors mainly due to the presence of large scale experiments in the used data base, which likes outside their applicable limits. Thus, this confirms the necessity to include more data related to large scale experiments in order to increase the range of applicability of various prediction equations for scour hole downstream rapid hydraulic structures.

5 CONCLUSIONS

Despite being important river training low head structures, there has not been much experiments on rapid hydraulic structures on large scale. However, many experimental studies are available for similar structures with ramps. This paper presents experimental work on rapid hydraulic structures investigating the characteristics of the downstream scour hole. Experimental data from this study have been used with other experimental data for similar ramp structures capturing the rapid and flow main characteristics with a total of 112 points including experimental data from large scale experiments on rapids. Genetic programming has been used to develop a relation for predicting maximum scour depth as a function of various rapid and flow parameters. Developed relation gave reasonable score in various indicators; it gave 0.84 in R-squared and 0.02 MSE with lowest errors amongst some of the available equations. While more data is still needed to enhance the prediction capability of the developed relation, however it can be used as preliminary estimates for scour hole formation downstream rapids while considering that errors are expected and shall have an uncertainty band of ± 0.67 orders of magnitude.

NOTATION

B	Rapid width
B_{UB}	Width of uncertainty band
d_{90}	Bed sediment size
F_{d90}	Densimetric Froude number
e	prediction error
h	Height difference between upstream and downstream of rapid
h_{max}	Maximum score hole depth
ρ	Water density
ρ_s	Sediment density
Q	Flow across rapid
g'	reduced gravity acceleration
S	rapid slope
Se	Standard deviation of prediction error
v	Flow velocity through rapid
σ	Coefficient of sediment variation

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