Estimating time to equilibrium scour at long abutment by using genetic programming

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ABSTRACT

Scouring around abutments and pier is a significant problem for bridges failure. The main objective of this study was the estimation of a predictor of time to equilibrium for long abutments (y/L<1) on the basis of Genetic programming (GP). An important number of experiments with long- lasting were used for GP modeling technics. All experiments were run under clear-water flow conditions and different sediments size. The main independent parameter selected after a sensitivity analysis to found best equation by GP. The performance of GP was found to be more effective when compared with other equations.

Keywords: Scour; abutment; genetic programming; equilibrium time; river; computer programming.

1 Introduction

Bridge piers and abutments are obstructions against flow and local scour hole is formed due to this structures. Scouring is major cause of failure of bridge piers and abutments. However, it takes time for scour holes to form and often adverse flow conditions at a site occur for only limited time frames.

Consequently, the estimation of the scour characteristics and development of scour with time at bridge foundation elements continues to be a concern for hydraulic engineers and researchers. Scour holes develop more slowly under clear-water conditions ($V/Vc < 1$, whereV is average approach flow velocity and Vc is critical flow velocity for sediment entrainment), scour holes develop more slowly, and it is well known that, the equilibrium scour depth is approached very slowly in time.

Recently the majority of scour researches conduct under long-lasting experiments. Chabert and Engeldinger (1956) suggested scouring reach to equilibrium scour depth when the depth does not particularly change with time. Ettema (1980) assumed scour process has three phases and in the third phase (equilibrium phase), scour depth "Appreciably" does not increase anymore.

Melville and Chiew (1999) defined equilibrium time as the time which in a 24–hour period, the rate of scour depth is limited to 5% of the pier diameter. Coleman et al. (2003) defined the time to equilibrium as the time at when in the succeeding 24–hour period, the reduction of scour rate to less than 5% of the flow depth or the abutment length(or pier diameter). Grimaldi (2005) supposed that time of equilibrium as the time when, rate of scour reduces to 5% of 0.33 pier diameter in 24 hours period.

The value of 5% is obviously arbitrary; other amount like 3% may be significantly increase equilibrium time. On the other hand the 24 hours usually considered are also arbitrary. During the past two decades, researchers have noticed that the use of soft computing techniques as an alternative to conventional statistical methods based on controlled laboratory or field data yielded significantly better results to equilibrium to estimate scour around hydraulic structures.

Other approaches such as artificial neural networks (ANNs) and neurofuzzy inference systems (ANFIS) Is used by Azmathullah et al. (2005 and 2008). Genetic programming (GP) is another method for cases of highly nonlinear and complex relationships among the input-output pairs. Azamathulla et al.(2010) has found a new equation to predict pier scour by using GP.

The purpose of this study is the definition of a predictor of time to equilibrium around long abutments (y/L<1) on the basis of genetic programming (GP) and compared GP techniques to other equation finally a new explicit equation is drive by GP.

2 Dimensional analysis

The scour depth around abutment in any point can be described by following parameters and independent variable:

$$d_s = F\lfloor y, U, U_c, g, \rho, \nu, d_{50}, \sigma_D, \rho_s, L, K_\theta, K_s, B, K_g, t \rfloor \quad (1)$$

where, y approach flow depth ; U mean flow velocity ; g is the acceleration due to gravity ρ and ν are the fluid density and kinematic viscosity, respectively; σ_D is the geometric standard deviation of the sediment particle size distribution; ρ_s is the sediment density; L is abutment length; Kθ and Ks are coefficients describing the alignment and the shape of the abutment; B is the channel width Kg is the coefficient describing the geometry of the channel cross-section; and t is the time. In this study assuming a thin vertical-wall abutment (Ks = 1), and a right angles from the channel side wall (Kθ = 1). On the other hand for wide rectangular channel and uniform flow condition K_g and B no longer effects scour. If d_{50}>0.6 mm, ρ_s be constant and σ_D <1.8 the bed material is compose of uniform non-ripple forming sand then ρ_s and σ_D can be eliminated. Finally equation (1) can rewire by following equation (Feal 2007).

$$\frac{d_s}{L} = F\left(\frac{L}{y}, \frac{U}{U_c}, \frac{UL}{\nu}, \frac{L}{d_{50}}, \frac{U\,t}{L}\right) \quad (2)$$

Assuming that in rivers viscous no longer influence on scouring problem, hence Equation (2) can be written as:

$$\frac{d_s}{L} = F\left(\frac{L}{y}, \frac{U}{U_c}, \frac{L}{d_{50}}, \frac{U\,t}{L}\right) \quad (3)$$

Another form of Equation (3) is suggested by Cardoso (2010).

$$\frac{d_s}{L} = F\left(\frac{L}{y}, \frac{U}{U_c}, \frac{d_{50} U\, t}{L^2}\right) \quad (4)$$

According Coleman et al. (2003), if $\frac{L}{d_{50}} > 100$ influence this term on the scour can be negligible therefore another from of Equation (2) is:

$$\frac{d_s}{L} = F\left(\frac{L}{y}, \frac{U}{U_c}, \frac{U\,t}{L}\right) \quad (5)$$

Final time (t_e) and equilibrium scour depth (d_{se}) associated with this time, depend on the same parameters. Consequently in finite time whent= t_e and $d_s = d_{se}$ following equation can be used

$$\frac{U\,t_e}{L} = F\left(\frac{L}{y}, \frac{U}{U_c}, \frac{L}{d_{50}}\right) \quad (6)$$

$$\frac{U\,t_e}{L} = F\left(\frac{L}{y}, \frac{U}{U_c}\right) \quad (7)$$

Equation (6) and (7) can be used for estimate equilibrium time to thin vertical abutments and perpendicular (without any angle to flow) in a wide rectangular channel and uniform flow. Equation (7) is appropriate to abutment with $\frac{L}{d_{50}} > 100$. A summary of equations to estimate equilibrium time around short abutments (y/L>=1) and long abutments(y/L<1) is shown in Table 1. In this table equations are divided by $\frac{L}{d_{50}}, \frac{y}{L}$ *and* $\frac{U}{U_c}$ parameters.

In persent research Around 63 data were collected from Kwan (1984), Tey (1984) , Dongol (1994) and Colman (2003) studies to pridiction equilibrium time around long abutments (y/L<1) . This data is used to develop GP and find prediction equation.Table 2 summarizes the ranges of data available such as abutment lenght (L) , flow velocity (V), flow depth (y) and mean diameter of bed material (d_{50}).

3 Genetic programming

The concept of GP is borrowed from the process of evolution occurring in nature, where the species survive according to the principle of “survival of the fittest”. GP, a branch of the Genetic Algorithm (GA) is a method for learning the most “fit” computer programs by means of artificial evolution (Johari et al. 2006). In other words, its behavior forms a metaphor of the processes of evolution in nature. GP, similar to GA, initializes a population that compounds the random members known as chromosomes (individual). Afterward, fitness of each chromosome is evaluated with respect to a target value. The principle of Darwinian natural selection is used to select and reproduce “fitter” programs. The main difference between GP and GA is the representation of the chromosomes and final solution. A GA creates equal length strings of numbers (chromosomes) in the form of binary or real, which represent the solution. However, GP creates equal or unequal length computer programs that consist of variables (terminal) and several mathematical operators (function) sets as the solution. The function set of the system can be composed of arithmetic operations (+,–, /, *) and function calls such as (ex ,x, sin, cos , tan, log, sqrt, ln, power). Each function implicitly includes an assignment to a variable, which facilitates the use of multiple program outputs in GP, whereas in tree- based GP those side effects need to be incorporated explicitly (Brameier and Banzhaf 2001).

Table 1 Empirical Formula for Estimate Equilibrium Scour Time Around Abutment

No.	*WRITERS*	*Equation*	*U/Uc*	*y/L and L/d50*
C1	Cardoso et al.(2010)	$\frac{U\,t_e}{L}=3136\left(\frac{L}{d_{50}}\right)\left(\frac{y}{L}\right)^{-1.318}$	0.57~1.2	y/L<1 and *L/d50>100*
C2	Coleman et al.(2003)	$\frac{U\,t_e}{L}=10^6\left(\frac{U}{Uc}\right)^3\left(\frac{y}{L}\right)\left[3-1.2\left(\frac{y}{L}\right)\right]$	VARIABLE	y/L<1 and *L/d50>60*
C3	Coleman et al.(2003)	$\frac{U\,t_e}{L}=1.8\times10^6\left(\frac{U}{Uc}\right)^3$	VARIABLE	y/L ≥ 1 and *L/d50>60*
C4	Coleman et al.(2003)	$\frac{U\,t_e}{L}=10^6\left(\frac{y}{L}\right)\left[3-1.2\left(\frac{y}{L}\right)\right]$	0.9~0.99	y/L<1 and *L/d50>100*
C5	Coleman et al.(2003)	$\frac{U\,t_e}{L}=1.8\times10^6$	0.9~0.99	y/L ≥ 1 and *L/d50>100*
C6	Coleman et al.(2003)	$\frac{U\,t_e}{L}=1.8\times10^6\left(\frac{y}{L}\right)^{0.8}$	0.9~0.99	y/L<1 and *L/d50>100*

Table 2 Ranges of Data

	Minimum		*Minimum*		*Maximum*	
	Training	*Testing*	*Training*	*Testing*	*Training*	*Testing*
L(mm)	150	150	1750	302	5750	717
Y(mm)	38	50	110	75	200	100
V(m/s)	0.17	0.27	0.31	0.3	1.26	1.05
d_{50}(mm)	0.8	0.82	2.1	0.83	18	188

The GP used in this study utilizes a two-point string crossover. dom length is selected in both parents and exchanged between them. If one of the resulting children would exceed the maximum length, the crossover is abandoned and restarted by exchanging equalized segments (Brameier and Banzhaf 2001). An operand or an operator of an instruction is changed by mutation into another symbol over the same set.

The fitness of a GP individual may be computed by using the equation

$$f=\sum_{j=1}^{N}\left(\left|X_j-Y_j\right|\right) \tag{8}$$

Where Xj=value returned by a chromosome for the fitness case j; and Yj=expected value for the fitness case j. In GP, the maximum size of the program is usually restricted to avoid overgrowing programs without bounds (Brameier and Banzhaf 2001). This configuration was tested for the proposed GP model and was found sufficient. The best individual (program) of a trained GP can be converted into a functional representation by successive replacements of variables starting with the last effective instruction (Oltean and Groşan 2003).

In this paper ,three basic arithmetic operators (+,−,-,) and some basic mathematical functions (power) were used . A large number of generations were tested(5000). First, the maximum size of each program was specified as 256, starting with 64 instructions for the initial program.

The simplified analytic form of the proposed GP model may be expressed as:

$$\frac{U\,t_e}{L}=7.13\times10^6\left(\frac{y}{L}\right)^{0.6}\left(\frac{U}{U_C}\right)^{2.97}\left(\frac{L}{d_{50}}\right)^{-0.3} \tag{9}$$

4 Checking and training GP

The performance of GP in training and testing sets is validated in terms of the common statistical measures R^2 (coefficient of determination) , root-mean-square error (RMSE), average error (AE), and average absolute deviation (δ)

$$R^2=\left(\frac{\sum xy}{\sqrt{\sum x^2\sum y^2}}\right)^2 \tag{10}$$

$$RMSE=\left(\frac{\sum(X-Y)^2}{n}\right)^{1/2} \tag{11}$$

$$AE = \left(\frac{\sum (\frac{X - Y}{X})100}{n} \right) \quad (12)$$

$$\delta = 100 \left(\frac{\sum |Y - X|}{\sum X} \right) \quad (13)$$

Where x=($X - \overline{X}$); y=($Y - \overline{Y}$); X=observed values; $\overline{X}$ =mean of X; Y =predicted value; $\overline{Y}$ =mean of Y; and n=number of samples.

First, an attempt was made to assess the significance or influence of each input parameter on Ut_e/L. Table 2 compares the GP models, with one of the independent parameters removed in each case. These three independent parameters have non-negligible influence on Ut_e/L and so the functional relationship given in Eq. (6) is used for GP modeling in this study. The GP approach resulted in highly nonlinear relationship between Ut_e/L and the input parameters with high accuracy and relatively low error.

Table 2 Analysis of Sensitivity for Independent Parameters

FOUNCTION	R^2	RMSE	AE
$Ut_e / L = f(L/y, U/U_c, L/d_{50})$	0.91	0.36	-0.086
$Ut_e / L = f(L/y, U/U_c)$	0.87	0.44	-0.119
$Ut_e / L = f(U/U_c, L/d_{50})$	0.80	0.53	-0.212
$Ut_e / L = f(L/y, L/d_{50})$	0.78	0.56	-0.213

The testing performance of the proposed GP model with three independent parameter revealed a high generalization capacity with R^2=0.91 and RMSE=0.36 and AE=−0.086.

5 Results and discussion

In long abutment Figure 1a , all of the data are plotted for which $U/U_c = 0.9 \sim 0.99$, $d_{50}/L > 100$, to show the comparsion between GP results and two Coleman equations (Eq. C4 and C6 in Table 1).

An excellent prediction, made by the GP, can be observed. The result of statistical analysis for three parameter of R^2 ,AE , δ is showed in Table 3. Comparisons of performance based on error statistics and scatter plots showed that GP model is generally model has lower absolute error as compared to other equations.

Table 3 Statistical Analysis for Data in Condition of U/Uc=0.9~0.99

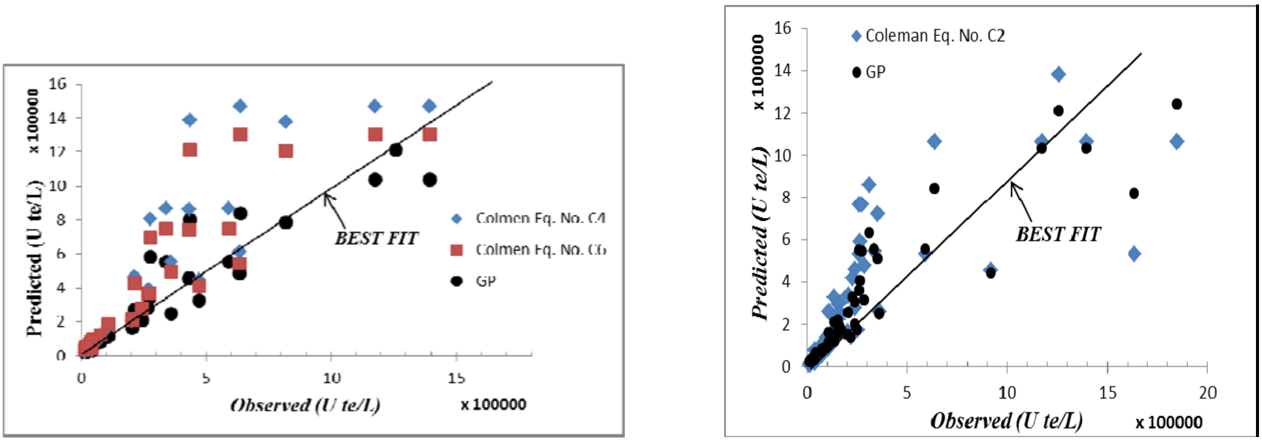
No.	Equation	conditions	R^2	AE(%)	δ(%)
C4	$\frac{U t_e}{L} = 10^6 \left(\frac{y}{L}\right)\left[3 - 1.2\left(\frac{y}{L}\right)\right]$	y/L<1 and L/d_{50}>100	0.89	-33	54
C6	$\frac{U t_e}{L} = 1.8 \times 10^6 \left(\frac{y}{L}\right)^{0.8}$	y/L<1 and L/d_{50}>100	0.89	-46	44
GP	$\frac{U t_e}{L} = 7.13 \times 10^6 \left(\frac{y}{L}\right)^{0.6} \left(\frac{U}{U_C}\right)^{2.97} \left(\frac{L}{d_{50}}\right)^{-0.3}$	y/L<1 and L/d_{50}>100	0.93	-10.5	24

Referring to Figure 1a and Table 3, GP outperforms in high-value predictions, as reflected in higher R^2 (0.93), and lower AE (-10.5%) and minimum δ (24%) compared to C4 euqation (R^2=0.89 , AE=-33% and δ=54%), and the C6 equations (R^2=0.89, AE=-46% and δ=44%).

In Figure 1b illustrate, amount of $U t_e/L$ for all range of U/Uc (between 0.46 to 0.99) which $d_{50}/L > 60$. Statistical results in Table 4 for this data revealed GP model has high acurrently (R^2 =0.93, AE=-16.07% and δ =32.08) as compared to C2 (R^2 =0.54, AE=-28.56% and δ =48.78) equation.

Table 4 Statistical Analysis for Data in Condition of U/Uc=0.46~0.99

No.	Equation	conditions	R^2	AE(%)	δ(%)
C2	$\frac{U t_e}{L} = 10^6 \left(\frac{U}{Uc}\right)^3 \left(\frac{y}{L}\right)\left[3 - 1.2\left(\frac{y}{L}\right)\right]$	y/L<1 and L/d_{50}>60	0.54	-28.56	48.78
GP	$\frac{U t_e}{L} = 7.13 \times 10^6 \left(\frac{y}{L}\right)^{0.6} \left(\frac{U}{U_C}\right)^{2.97} \left(\frac{L}{d_{50}}\right)^{-0.3}$	y/L<1 and L/d_{50}>60	0.77	-16.07	32.08



(a) $U/U_c = 0.9 \sim 0.99$, $d_{50}/L > 100$, $y/L < 1$ (b) $U/U_c = 0.46 \sim 0.99$, $d_{50}/L > 60$, $y/L < 1$

Figure 1 Comparison of Predict by GP and Coleman equations

It must noted that at larger $U t_e/L$ error measures are more sensitive to $U t_e/L$ observations. An almost perfect agreement with the observed small values ($U t_e/L < 3$) and GP predictions is clearly showed in Figures 1a and 1b.

Finally in Figure 2 to assess the performance of the GP model, the observed nondimensional finite time were plotted against the predicted ones for all data by using equation (9). There are very well fitness by used GP for all data without any limitation in sediment size and velocity. As shown in the results equation (9) can predict equilibrium time for long abutment in all conditions with more accurately.

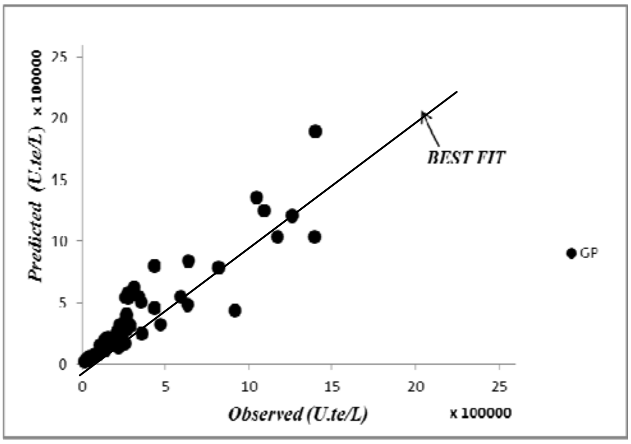


Figure 2 Observed versus predicted finite time

6 Conclusions

The application of the relatively new soft computing approach of GP to predict the equilibrium time of scour depth around long abutment was described. A GP was developed to predict the values of equilibruim time from the laboratory measurements. A new approach was presented to estimate the equilibrium time of scouring around long abutment (y/L<1) with the GP modeling techniques.

The application of the GP in this study is another important contribution to finite time estimation methodologies for abutments. The present study indicates that GP can predict nondimentional equilibrium time with more accurately for condition without any limitation in sediment size or velocity. The overall performance of the GP model is superior to other equations.

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