Prediction of equilibrium scour time around long abutments

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Scouring around abutments and piers is a significant problem in bridge failure. The main objective of this study is to estimate the equilibrium time around long vertical abutments using genetic programming (GP). The data from a large number of clear-water scour experiments in uniform sand beds were collected for GP modelling techniques. To predict the equilibrium scour time, three independent parameters were selected using sensitivity analysis: \( \frac{y}{L} \), \( \frac{U}{U_c} \) and \( \frac{L}{d_{50}} \). The results based on GP were compared with those of the artificial neural networks (ANNs) and empirical methods. Statistical tests indicate that, although the ANN method produced better results compared with GP and non-linear regression techniques, the GP equation is more useful for practical purposes.

1. Introduction

The scouring of abutments and piers is a major cause in the collapse of bridge foundations. The presence of abutments in front of the flow may cause a huge change in the flow pattern. A scour hole develops around an abutment due to complex vortex flow. This vortex flow develops the scour hole in three places – in front of, to the side of and downstream of the abutment (Dey and Barbhuiya, 2005). The trend of local scour around abutments is time dependent and hence a time-dependent analysis of scouring at abutments is important for hydraulic engineers. Because many abutments cross part of the floodplain channel and scour generally occurs under clear-water conditions in such places, the main concern of this study is to determine the equilibrium time around abutments under clear-water conditions.

Ettema (1980), Melville and Chiew (1999) and Coleman et al. (2003) conducted significant experimental investigations on time variation. The development of scour comprises a primary phase followed by an equilibrium condition in which the scour depth no longer shows any practical change. Chabert and Engeldinger (1956) suggested that scouring reaches the equilibrium scour depth when the depth does not increase significantly with time. Ettema (1980) assumed that the scour process has three phases. In the first and second phases, the scour depth develops rapidly but, in the third phase (the equilibrium phase), the scour depth does not increase ‘appreciably’. Melville and Chiew (1999) defined the equilibrium time as the time at which, in a 24 h
period, the rate of increase of the scour depth does not exceed 5% of the abutment length. Coleman et al. (2003) defined the time to equilibrium as the time when, in the succeeding 24 h period, the scour rate decreases to less than 5% of the flow depth or the abutment length (pier diameter).

Over the past two decades, researchers have noted that the use of soft computing techniques such as artificial neural networks (ANNs), genetic programming (GP) and gene expression programming (GEP) as alternatives to conventional statistical methods based on laboratory data or field data yielded significantly better estimates of scour around hydraulic structures. Toth and Brandimarte (2011) used an ANN to predict local scour around bridge piers under live bed and clear-water conditions. The results showed that the ANN predictions outperformed the estimates obtained using a conventional formula. An adaptive neuro-fuzzy inference system (ANFIS) is another predictive approach that has been used to predict scour depth around abutments in sand and an armoured layer (Muzzammil, 2010; Muzzammil and Alam, 2010). A comparison of results showed that the ANFIS method performed better than regression equations in forecasting abutment scour.

The GP method is another approach to prediction problems in river engineering, especially for cases that involve complex and highly non-linear relationships between data. Mohammadpour et al. (2011) and Ab Ghani et al. (2011) employed GP to predict scour depth around abutments and piers. They showed that GP was more accurate than the use of regression equations.

GEP is an extension of GP that evolves computer programs. Azamathulla (2011) used a GEP model to predict abutment scour, and the results were found to be more accurate than the ANN method. In the case of bridge abutments, the study of time evolution using GP or GEP has received less attention than other cases. However, it has been realised that the time dependence of local scour has some significance, especially in forecasting the scour depth for a given flow duration. The purpose of this paper is the prediction of the equilibrium time around long abutments ($y/L < 1$) on the basis of GP. Comparisons with other methods are made.

2. Dimensional analysis

The equilibrium scour depth around an abutment at any point can be described by the following parameters and independent variables

$$d_e = F(y, U, U_c, g, \rho, v, d_{50},$$

1. $\sigma_d, \rho_s, L, K_\theta, K_s, B, K_g, t$)

where $y$ is the approach flow depth, $U$ is the mean flow velocity, $U_c$ is the critical velocity for the beginning of motion of the bed material, $g$ is acceleration due to gravity, $\rho$ and $v$ are the fluid density and kinematic viscosity respectively, $d_{50}$ is the median size of the bed material, $\sigma_d$ is the geometric standard deviation of the sediment particle size distribution, $\rho_s$ is the sediment density, $L$ is the abutment length, $K_\theta$ and $K_s$ are coefficients describing the alignment and the shape of the abutment respectively, $B$ is the channel width, $K_g$ is a coefficient describing the geometry of the channel cross-section and $t$ is time.

In this study, it is assumed that a vertical wall abutment is used ($K_s = 1$) and that the abutment is at right angles from the channel side wall ($K_\theta = 1$). However, for wide rectangular channels and uniform flow conditions, $K_\theta$ and $B$ no longer affect the scour. If $d_{50} > 0.6$ mm, $\rho_s$ is constant, $\sigma_d < 1.8$ and the bed material is composed of uniform non-ripple-forming sand, then $\rho_s$ and $\sigma_d$ can be eliminated. Finally, using Buckingham’s $\pi$ theorem, Equation 1 can be rewritten as (Cardoso and Fael, 2010)

$$d_e = F\left(\frac{L}{Uc}, \frac{UL}{d_{50}}, \frac{Ut}{L}\right)$$

Assuming that the approach flow around the abutments is fully turbulent, it can be claimed that the Reynolds number ($UL/v$) has no influence on the scour. Hence, Equation 2 can be written as

$$d_e = F\left(\frac{L}{Uc}, \frac{L}{d_{50}}, \frac{Ut}{L}\right)$$

According to Coleman et al. (2003), if $L/d_{50} > 100$, the influence of this term on the scour is also negligible. Therefore, another form of Equation 2 is

$$d_e = F\left(\frac{L}{Uc}, \frac{Ut}{L}\right)$$

The equilibrium time ($t_e$) and the scour depth associated with this time ($d_e$) depend on the same parameters (Cardoso and Fael, 2010). Consequently, within a finite time when $t = t_e$ and $d_e = d_{50}$

$$\frac{Ute}{L} = F\left(\frac{L}{Uc}, \frac{L}{d_{50}}\right)$$

$$\frac{Ute}{L} = F\left(\frac{L}{Uc}\right)$$

Equations 5 and 6 can be used to estimate the equilibrium time for vertical and perpendicular abutments (without any angle to the flow) in a wide, rectangular channel with uniform flow. Equation 6 is appropriate for abutments with $L/d_{50} > 100$. 

$$\frac{Ute}{L} = F\left(\frac{L}{Uc}\right)$$
A summary of equations to estimate the equilibrium time around short ($y/L > 1$) and long abutments ($y/L < 1$) is shown in Table 1 according to varying $L/d_{50}$, $y/L$ and $U/U_c$. Extensive library datasets were obtained for the purposes of model development to predict the equilibrium time around long abutments ($y/L < 1$) from earlier studies by Kwan (1984), Tey (1984), Dongol (1994), Ballio and Orsi (2001), Coleman et al. (2003) and Dey and Barbhuiya (2005). These data were used to develop the equations using the GP method, ANN and non-linear regression. Table 2 summarises the ranges of data available for testing and training that were used in the different models.

### 3. Regression model results
A new regression equation was developed to predict the equilibrium time based on three model inputs. A least-squares fit to these observations yielded

$$\frac{U_{te}}{L} = 6.76 \times 10^6 \left(\frac{y}{L}\right)^{0.58} \left(\frac{U}{U_c}\right)^{2.95} \left(\frac{L}{d_{50}}\right)^{-0.31}$$

The constants in this equation were determined on the basis of the least-squares fit to 80% of the randomly selected values. The results of Equation 7 are discussed in Section 7.

### 4. Development of the ANN model
A neural network model generally includes three layers of neurons (the input, hidden and output layers), with each neuron acting as an independent computational element. ANNs provide a random mapping between an input and an output vector. ANNs derive their strength by using the large number of degrees of freedom that depends on their architecture (Ab Ghani et al. 2011). The network training is the main step in an ANN. Hence, by using sets of input and output pairs as feeds, the network was

<table>
<thead>
<tr>
<th>Research</th>
<th>Equation</th>
<th>$U/U_c$</th>
<th>$y/L$</th>
<th>$L/d_{50}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equation C1</td>
<td>$\frac{U_{te}}{L} = 3136\left(\frac{L}{d_{50}}\right)^{-1.318}$</td>
<td>0.57–1.2</td>
<td>&lt;1</td>
<td>&gt;100</td>
</tr>
<tr>
<td>Equation C2</td>
<td>$\frac{U_{te}}{L} = 10^6\left(\frac{U}{U_c}\right)^3 \left[3 - 1.2\left(\frac{y}{L}\right)\right]$</td>
<td>Variable</td>
<td>&lt;1</td>
<td>&gt;60</td>
</tr>
<tr>
<td>Equation C3</td>
<td>$\frac{U_{te}}{L} = 1.8 \times 10^6\left(\frac{U}{U_c}\right)^3$</td>
<td>Variable</td>
<td>≥1</td>
<td>&gt;60</td>
</tr>
<tr>
<td>Equation C4</td>
<td>$\frac{U_{te}}{L} = 10^6\left(\frac{y}{L}\right)^3 \left[3 - 1.2\left(\frac{y}{L}\right)\right]$</td>
<td>0.9–0.99</td>
<td>&lt;1</td>
<td>&gt;100</td>
</tr>
<tr>
<td>Equation C5</td>
<td>$\frac{U_{te}}{L} = 1.8 \times 10^6$</td>
<td>0.9–0.99</td>
<td>≥1</td>
<td>&gt;100</td>
</tr>
<tr>
<td>Equation C6</td>
<td>$\frac{U_{te}}{L} = 1.8 \times 10^6\left(\frac{y}{L}\right)^{0.8}$</td>
<td>0.9–0.99</td>
<td>&lt;1</td>
<td>&gt;100</td>
</tr>
</tbody>
</table>

Table 1. Empirical formula to estimate equilibrium time around abutment

<table>
<thead>
<tr>
<th>Minimum</th>
<th>Median</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>$L$: mm</td>
<td>100</td>
<td>300</td>
</tr>
<tr>
<td>$y$: mm</td>
<td>38</td>
<td>100</td>
</tr>
<tr>
<td>$U$: m/s</td>
<td>0.17</td>
<td>0.30</td>
</tr>
<tr>
<td>$d_{50}$: mm</td>
<td>0.80</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Table 2. Ranges of data
trained and the values of connection weights, biases or centres were determined. Training may require many epochs and is conducted until the training sum of squares error satisfies a specified error goal.

In this study, a simple feed forward back propagation (FFBP) model with different hidden layers and neurons were developed. Out of the total dataset, approximately 80% (60 sets) were selected randomly and used for training. The remaining 20% (12 sets) were employed for testing. The best network configuration is identified by minimising the difference between the predicted values of the neural network and the desired outputs, which was achieved by changing the number of neurons and hidden layers. Because the number of nodes in the hidden layer is unknown, the networks were trained with different numbers of neurons to select the best network, and the results were compared on the basis of the average absolute deviation (Figure 1). The process of training was stopped when either the number of iterations exceeded a prescribed maximum of 3000 or a suitable level of error was achieved. Figure 1 shows the error variation as a function of the number of neurons in the hidden layer. When the number of neurons in the hidden layer is increased, the error decreases dramatically. The result shows that using a one-hidden-layer FFBP with seven neurons in the hidden layer yields the best results, particularly when a minimum number of neurons is necessary. Figure 2 indicates the architecture of the neural network with three input neurons, seven neurons in the hidden layer and one neuron at the output.

5. Genetic programming

Inspired by biological evolution, GP is a methodology for automatically solving problems using computers. GP, a type of genetic algorithm (GA), is a pattern for learning the most ‘fit’ computer programs by means of artificial evolution (Johari et al., 2006). The GP and GA methods are similar in most aspects. They both initialise a population and compound the random members known as chromosomes (individuals). Then, the fitness of each chromosome is evaluated with respect to a final amount. Afterwards, to reproduce ‘fitter’ programs, the concept of Darwinian natural selection is used. The main difference between GP and the GA is the representation of the solution. GP creates unequal and equal computer programs that consist of several mathematical operators and variable sets as the solution. However, the GA creates equal-length chromosomes in the form of binary or real numbers, which represent the solution. The system can be composed of function calls (such as \( e^x, x, \sin, \cos, \tan, \log, \sqrt{x}, \ln, \) power) and mathematical operations (+, -, \( \div \), \( \times \)). Each function implicitly includes an assignment to a variable, which facilitates the use of multiple program outputs in GP; in tree-based GP, those side effects must be incorporated explicitly (Brameier and Banzhaf, 2001).

In this research, a two-point string crossover was utilised in the GP. A segment of random length and random position is used in both parents and exchanged between parents. The crossover is abandoned and restarted by exchanging equalised segments when one of the resulting children exceeds the maximum length. The instruction operator is modified by mutation into another symbol over the same set (Brameier and Banzhaf, 2001). The following equation was used to compute the fitness of a GP individual

\[
f = \sum_{j=1}^{N} \left| X_j - Y_j \right|
\]

Figure 1. Variation of \( \delta \) in terms of the number of neurons in FFBP networks with one hidden layer

Figure 2. Neural network architecture
where $Y_j$ is the expected value for fitness case $j$ and $X_j$ is the value returned by a chromosome for fitness case $j$.

In GP, to avoid overgrowing programs, the maximum size of the program is generally restricted (Brameier and Banzhaf, 2001). This configuration was tested for the proposed GP model and was found to be 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 Grosan, 2003). In this paper, one basic mathematical function (power) and three basic arithmetic operators (plus, minus, negative) and a large number of generations (5000) were used for testing. First, the maximum size of each program was specified as 256, starting with 64 instructions for the initial program. Table 3 shows the operational parameters and functional set used in the GP modelling.

### 6. Validation of results

To validate the results for the training and testing sets, several common statistical measures such as the coefficient of determination ($R^2$), average error (AE) and average absolute deviation ($\delta$) are used. These are given by

\[
R^2 = \left( \frac{\sum xy}{\left( \sum x^2 \sum y^2 \right)^{1/2}} \right)^2
\]

9.

\[
AE = \frac{\sum [(X - Y)/X]100}{n}
\]

10.

\[
\delta = 100 \frac{\sum |Y - X|}{\sum X}
\]

11.

where $x = (X - \bar{X})$, $y = (Y - \bar{Y})$, $X$ are the observed values, $\bar{X}$ is the mean of $X$, $Y$ is the predicted value, $\bar{Y}$ is the mean of $Y$ and $n$ is the number of samples.

First, an attempt was made to assess the significance or influence of each input parameter on $U_t/L$. Table 4 compares the GP models with one of the independent parameters removed in each case for randomly selected data. These three independent parameters have a non-negligible influence on $U_t/L$, and thus the functional relationship given in Equation 5 was used for GP modelling in this study. The GP approach resulted in a highly non-linear relationship between $U_t/L$ and input parameters with high accuracy and relatively low error. The testing performance of the proposed GP model with three independent parameters shown in Table 4 revealed a high generalisation capacity with $R^2 = 0.83$, $AE = -18.63$ and $\delta = 29.67$. The simplified analytic form of the proposed GP model may be expressed as

**Table 3. Parameters of the optimised GP model**

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_1$</td>
<td>Population size</td>
<td>500</td>
</tr>
<tr>
<td>$P_2$</td>
<td>Mutation frequency: %</td>
<td>96</td>
</tr>
<tr>
<td>$P_3$</td>
<td>Crossover frequency: %</td>
<td>50</td>
</tr>
<tr>
<td>$P_4$</td>
<td>Function set</td>
<td>plus, minus, negative, power</td>
</tr>
<tr>
<td>$P_5$</td>
<td>Number of generation</td>
<td>25</td>
</tr>
<tr>
<td>$P_6$</td>
<td>Block mutation rate: %</td>
<td>30</td>
</tr>
<tr>
<td>$P_7$</td>
<td>Instruction mutation rate: %</td>
<td>30</td>
</tr>
<tr>
<td>$P_8$</td>
<td>Instruction data mutation rate: %</td>
<td>40</td>
</tr>
<tr>
<td>$P_9$</td>
<td>Homologous crossover: %</td>
<td>95</td>
</tr>
<tr>
<td>$P_{10}$</td>
<td>Program size</td>
<td>Initial 64, maximum 256</td>
</tr>
</tbody>
</table>

**Table 4. Analysis of the sensitivity for independent parameters**

<table>
<thead>
<tr>
<th>Function</th>
<th>$R^2$</th>
<th>AE: %</th>
<th>$\delta$: %</th>
</tr>
</thead>
<tbody>
<tr>
<td>$U_t/L = f(U/U_c, L/d_{50})$</td>
<td>0.46</td>
<td>-28.65</td>
<td>35.32</td>
</tr>
<tr>
<td>$U_t/L = f(L/y, L/d_{50})$</td>
<td>0.51</td>
<td>-26.31</td>
<td>33.27</td>
</tr>
<tr>
<td>$U_t/L = f(L/y, U/U_c)$</td>
<td>0.71</td>
<td>-21.8</td>
<td>31.75</td>
</tr>
<tr>
<td>$U_t/L = f(L/y, U/U_c, L/d_{50})$</td>
<td>0.83</td>
<td>-18.63</td>
<td>29.67</td>
</tr>
</tbody>
</table>

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Table 5 shows a comparison of GP and other methods for the randomly selected dataset used in Table 4.

Figures 3(a) and 3(b) show the performance of GP compared to the Coleman equations and the ANN for two different ranges of data. Excellent predictions were made by the ANN and GP methods, which are quantitatively reflected in the statistical measures in Tables 6 and 7 between GP and other methods.

7. Results and discussion

Figure 3(a) shows data pertaining to a long abutment for which \( U/L = 0.86 - 0.99 \) and \( L/d_{50} \geq 100 \) to show the comparison of the results of GP, the ANN and the Coleman equations (Equation C4 in Table 1). The predictions of the ANN and GP are excellent. The results of statistical analysis for \( R^2, \text{AE} \) and \( \delta \) are shown in Table 6. As indicated by Figure 3(a) and Table 6, the ANN outperforms in high-value predictions, as reflected in its higher \( R^2 (0.897) \), low \( \text{AE} (11.35\%) \) and sufficient value for \( \delta \)

<table>
<thead>
<tr>
<th>Function</th>
<th>( R^2 )</th>
<th>( \text{AE}): %</th>
<th>( \delta): %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coleman (Equation C4)</td>
<td>0.61</td>
<td>-27.80</td>
<td>46.27</td>
</tr>
<tr>
<td>Regression</td>
<td>0.81</td>
<td>-21.79</td>
<td>30.48</td>
</tr>
<tr>
<td>GP</td>
<td>0.83</td>
<td>-18.63</td>
<td>29.67</td>
</tr>
<tr>
<td>ANN</td>
<td>0.882</td>
<td>-5.14</td>
<td>20.07</td>
</tr>
</tbody>
</table>

Table 5. Statistical analysis for randomly selected data

<table>
<thead>
<tr>
<th>Equation</th>
<th>( R^2 )</th>
<th>( \text{AE}): %</th>
<th>( \delta): %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equation C4</td>
<td>0.79</td>
<td>-61.0</td>
<td>56</td>
</tr>
<tr>
<td>Equation C6</td>
<td>0.80</td>
<td>-67</td>
<td>45.6</td>
</tr>
<tr>
<td>Regression</td>
<td>0.85</td>
<td>-18.1</td>
<td>25.3</td>
</tr>
<tr>
<td>GP</td>
<td>0.86</td>
<td>-16.2</td>
<td>23.4</td>
</tr>
<tr>
<td>ANN</td>
<td>0.897</td>
<td>-11.35</td>
<td>20.24</td>
</tr>
</tbody>
</table>

Table 6. Statistical analysis for data when \( U/U_c = 0.86 - 0.99 \)
under the conditions \( y/L < 1 \) and \( L/d_{50} > 100 \)
(20.24%), compared with the Equation C4 ($R^2 = 0.79$, 
$\text{AE} = -61\%, \delta = 56\%$), Equation C6 ($R^2 = 0.80$, $\text{AE} = -67\%$, 
$\delta = 45-6\%$) and the regression equation ($R^2 = 0.85$, 
$\text{AE} = -18-1\%, \delta = 25-3\%$). In this range of data, comparisons of 
performance based on scatter plots and error statistics revealed 
that the prediction accuracy of the proposed GP model is generally comparable to that of the ANN model.

Figure 3(b) plots $U_t/L$ for $U/U_c$ between 0-46 and 0-95 and 
$L/d_{50} > 60$. The statistical results in Table 7 for these data 
revealed that the GP model has a high accuracy ($R^2 = 0.77$, 
$\text{AE} = -28.56\%, \delta = 48.78\%$) compared with the Coleman equation 
(Equation C2) ($R^2 = 0.54$, $\text{AE} = -28.56\%, \delta = 48.78\%$). 
Table 7 shows that the GP model can predict the equilibrium time 
better than regression equations although, in this range of data, the ANN gives a higher accuracy than GP.

As indicated by Figure 3(b) and Table 7, for a long abutment 
$U/U_c = 0.46-0.95$ and $L/d_{50} > 60$, the ANN outperforms in best-
value predictions (equilibrium time), as reflected in a lower 
AE = -14-58% and a high $R^2 = 0.811$ compared with the regression-based equation ($AE = -16-80\%$, $R^2 = 0.76$) and the 
Coleman equation ($AE = -28.56\%$, $R^2 = 0.54$). It should be 
mentioned that these error measures are more sensitive to errors 
for larger amounts of equilibrium time observations.

The error measures are more sensitive to larger values of 
$U_t/L$, and Figures 3(a) and 3(b) show that the equilibrium scour 
time around an abutment is more sensitive to $U/U_c$. Almost perfect 
agreement occurs between predictions and observations for small 
values of the equilibrium time ratio ($U_t/L < 5$). At larger $U_t/L$, 
the error measures are more sensitive to $U_t/L$ observations. 
Almost perfect agreement with the observed small values ($U_t/L < 5$) and GP predictions is clearly shown in Figure 4 but in this 
data range the ANN prediction is also valuable. Figure 5 shows the performance of the GP compared with Equation C2, the ANN 
and the non-linear regression equation for all ranges of data. 
Comparisons of performance based on error statistics and scatter 
plots showed that the ANN and GP models generally have the best 
results in terms of predicting the abutment equilibrium time.

8. Conclusions
The prediction of the scour equilibrium time at abutments is 
esential to preserve bridges during floods. ANN, regression and 
GP models were developed to predict the values of the relative 
equilibrium scour time using collected data. The GP method 
appeared to be more attractive if the expected $R^2$ is selected as a 
criterion. The GP model predicted a scour time that was fairly 
accurate and comparable with the results of earlier works based 
on ANNs and superior to the regression equations and previously 
used equations. This study indicates that ANNs can be used to 
predict non-dimensional equilibrium times around abutments with 
more accuracy for any condition without limitations on sediment
size or velocity but, for practical purposes, the GP-based formula is more useful.

REFERENCES


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