GENETIC PROGRAMMING FOR PREDICTION OF LOCAL SCOUR AT VERTICAL BRIDGE ABUTMENT

S. A. Begum[1], A. K. Md. Fujail[2], A. K. Barbhuiya[3]

[1]*Department of Computer Science, Assam University, Silchar, Assam, India*
[2]*Department of Computer Science, Assam University, Silchar, Assam, India*
[3]*Department of Civil Engineering, National Institute of Technology, Silchar, Assam, India*

Abstract

Local scour around bridge abutment is a common problem encountered worldwide. Extensive laboratory and field studies have been carried out in this field and the equations derived so far are applicable to particular circumstances only. This paper presents an alternative to the empirical equations for Prediction of Local Scour at Vertical Bridge Abutment in the form of genetic programming (GP). The performance of the developed models has been evaluated using Root Mean Square Error and Correlation Coefficient. The accuracy of the trained model has been compared with the empirical formulae available in the literature. The performance of GP model is found to be more accurate than the empirical equations.

Keywords: *Genetic programming, neural network, scour depth, abutment.*

----------***----------

1. INTRODUCTION

Scour is the erosion caused by water of the soil around obstruction. The magnitude of the scour is multiplied when the natural flow is disturbed due to the presence of some obstructions like bridge pier, bridge abutment, spur etc. Failure of bridges due to local scour at their foundation is a common occurrence and each year a large amount is spent to repair or replace bridges whose foundations have been undercut by the scouring action of stream flow [1, 2]. Bridge foundation consists of abutments and piers. Probably the number of existing bridge abutments is much more than the numbers of bridge piers as most of the bridges are of single span. In a report, published by the Department of Scientific and Industrial Research (DSIR) of New Zealand [3], it is reported that almost 50% of total expenditure was made to repair and maintain bridge damage, out of which 70% was spent to repair abutment scour. Thus, scour around bridge abutment is a severe hazard to the performance of bridges. Considerable investigations on pier scour have been carried out and a reliable design method is now available [4]. However, evaluating scour around abutment is in preliminary stage. It is essential to understand the scour in the design of foundations of structures as well as scour protection work. Without a detailed understanding of scour, failures are more likely to occur. Extensive experimental investigation has been conducted to understand the complex process of scour and to determine a method of predicting scour depth for various abutment situations but no generic formula has been developed yet that can be applied to all abutment conditions to determine the extent of scour that may develop. Although, numerous empirical formulae have been presented to estimate equilibrium scour depth at bridge abutment [5-6], each varies significantly, highlighting the fact that there is a lack of knowledge in predicting scour depth and that a more universal solution would be beneficial. Only a few number of studies relating to the application of soft computing methods in the field of scour around bridge abutment are available in the literature. Kheireldin [7] used the artificial neural network (ANN) to predict the maximum local scour depth around bridge abutments. It reported that the ANN approach performed well for one set of data and its performance was not satisfactory for another set of data. Begum *et al.* [8] developed Radial basis function (RBF) network to predict scour depth around vertical bridge abutment and it is reported that the performance of RBF network is much better than the existing empirical formulae. Begum *et al.* [9] also developed Multilayer perceptron (MLP) and RBF network to predict scour around semicircular abutment. In the experimental results, it is shown that ANN models perform better than empirical equations.

In this paper we present an alternative approach for Prediction of Local Scour at Vertical Bridge Abutment in the form of Genetic Programming (GP).

2. GENETIC PROGRAMMING

GP is an extension to genetic algorithms (GAs) proposed by Koza [10] who defines GP as a domain-independent problem-solving approach in which computer programs are evolved to solve or approximately solve problems based on the Darwinian principle. GP creates computer programs that consist of variables and several mathematical operators (function) sets as the solution. The function set of the model can be composed of arithmetic operations (+, −, /, *) and function calls (such as ex,

sin, cos, log, ln, sqrt, power). In the present GP implementation, two-point string crossover and single point mutation is used. In crossover, a segment of random position and random length is selected in both parents and exchanged between them. In mutation, an operator or operand is replaced with another operator symbol over the same set. The fitness of a GP individual may be computed by using the equation

$$E = \sum_{i=1}^{N} (o^i - t^i)^2 \qquad (1)$$

Where ti = value returned by a chromosome and oi = target value for the ith fitness case.

In the present work, the maximum size of the program is restricted by setting the maximum depth of the tree. The best individual of the trained GP model can be identified based on Eq. 1 and can be converted into a functional representation.

A few number of studies related to the application of GP in hydraulic engineering are available in literature. Guven and Gunal [11] used GP to predicted local scour downstream of hydraulic structures. It was reported that the performance of GP was found more effective when compared to regression equations and ANNs in predicting the scour depth at bridge piers. Guven et al.[12] applied linear genetic programming (LGP) to predict scour around circular piles and the results were better than Adaptive neuro fuzzy inference system (ANFIS) and regression-based equations. Azamathulla et al. [13] estimated the scour depth around pier with GP. The performance of GP was found to be more effective when compared with the results of regression equations and ANNs modeling in predicting the scour depth around pipelines. Azamathulla et al. [14] also developed LGP model to compute scour below submerged pipeline. The results were better as compared to ANFIS and regression-based equations. Azamathulla [15] implemented GP model for prediction of scour depth downstream of sills. It was able to provide better estimation than existing predictors.

3. GP TO PREDICT MAXIMUM LOCAL SCOUR DEPTH AROUND ABUTMENT

Maximum equilibrium local scour depth around an abutment in a steady flow of uniform, cohesionless sediment depends on variables characterizing the fluid, flow, bed sediment and abutment. Thus, the maximum equilibrium scour depth can be described by the following functional relationship [16]:

$$d_{se} = f_1(U, \rho, \rho_s, g, l, \nu, h, d_{50}) \qquad (2)$$

where, U = average approach flow velocity, ρ = mass density of the fluid, ρ_s = mass density of the sediment, g = gravitational acceleration, l = abutment length, ν = kinematic viscosity, h=approaching flow depth, d_{50} = median grain size, d_{se} = equilibrium scour depth.

Since, ρ, ρ_s, g and ν are constant for given sediment and fluid, the relationship between d_{se} and its dependent variables can be expressed as:

$$d_{se} = f_2(l, d_{50}, h, U) \qquad (3)$$

The dataset for training the GP models were collected from the literature [16]. It consists of an experimental database comprising of five sets of data for vertical wall abutments. The dataset contains four independent parameters: l, d_{50}, h and U and one dependent parameter d_{se} i.e. depth of the scour. The whole dataset consists of 99 samples out of which 79 samples are considered for training and 24 samples are considered for testing.

The GP model is implemented in MATLAB 7.9 environment. To develop the model, l, d_{50}, h and U are considered as input parameter and d_{se} is considered as output parameter. The arithmetic operators (+, −, *, /) and mathematical functions (square root, power, log, exponentiation) were used. The population size of the model is specified as 150 and the maximum number of nodes in the GP tree was specified as 300. The tournament size was set as 2%. To get the optimal solution, GP model was tested with upto 4000 generations.

4. EXPERIMENTAL RESULTS

The performance of GP in training and testing sets is validated in terms of correlation coefficient (CC) and root mean square error (RMSE).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(o_i - t_i\right)^2} \qquad (4)$$

$$CC = \frac{\sum_{i=1}^{n}\left(o_i - \bar{o}\right)\left(t_i - \bar{t}\right)}{\sqrt{\sum_{i=1}^{n}\left(o_i - \bar{o}\right)^2 \sum_{i=1}^{n}\left(t_i - \bar{t}\right)^2}} \qquad (5)$$

where, o_i and t_i are network and target output for the ith input pattern, and $\bar{o}$, $\bar{t}$ are the average of network and target outputs and n is the total number of events considered. The model having minimum RMSE and maximum CC during testing is selected as optimum. Some of the training and testing cases are tabulated in Table 1.

Table 1 Training and Testing cases of GP (Population Size=150, Tournament Size=0.02)

Generation	Training		Testing	
	RMSE	CC	RMSE	CC
1000	0.0821	0.9153	0.0752	0.9153
2000	0.0647	0.9472	0.0596	0.9472
3000	**0.0492**	**0.9648**	**0.0351**	**0.9648**
4000	0.0510	0.9680	0.0373	0.9680

From table 1, it is seen that the GP model with 3000 generation provides the minimum RMSE and maximum CC for the training and testing case data and thus considered as the best case for the present experimentation. For the best case, the generated GP tree is shown is shown in Fig. 1. The corresponding arithmetic expression is as follows:

$$d_{se} = x_4 - x_1 * \log(\sqrt{x_2^{e^{x_1}}}) * (\log(e^{x_4}) + x_3 - x_1) \quad (6)$$

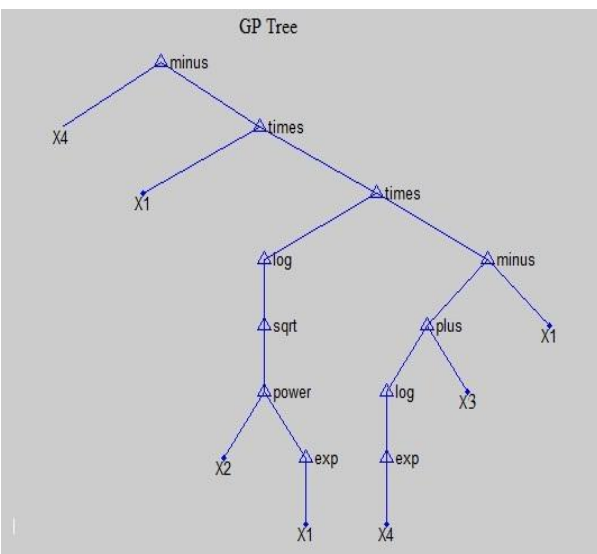
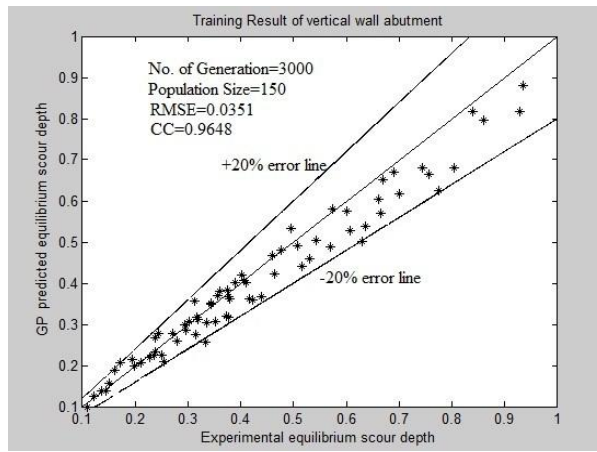


Fig. 1 GP Tree

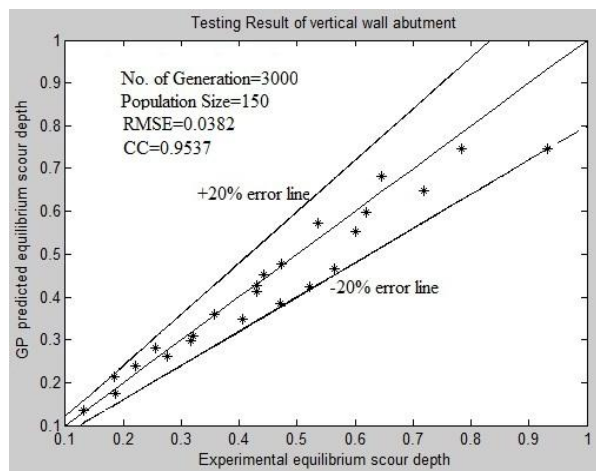
The best case of the GP model and the result of two of the empirical equations available in the literatures (Appendix A) are tabulated in Table 2. For the best case training and testing of GP model the actual versus the predicted scour depth is plotted in Fig 2. From Fig. 2, it is seen that the predicted values are within ±20% from the observed values. From Table 2, it is observed that the GP model is able to provide better results than the empirical equations developed by Froehlich [5] and Kandasamy *et al.* [6].

Table 2 GP versus empirical equations

Method	RMSE	CC
Froehlich[5]	0.3009	0.4018
Kandasamy and Melville[6]	0.1676	0.7054
GP	0.0351	0.9648



(a)



(b)

Fig. 2 The best case training and testing of GP Model

5. CONCLUSIONS

In the present work, GP is employed to predict the local scour at vertical bridge abutment. The GP model with population size of 150, tournament size=0.02 and 3000 iteration is found to be optimal. The performance of the present GP model is compared with two of the existing empirical equations over the same dataset. The GP tree and the mathematical expression generated by the best case GP model are also presented. From the results, it is observed that the predicted scour depth of the

GP model is more accurate than the empirical equations for the dataset used in the present work.

FUTURE WORK

The present GP configuration can further be fine tuned to improve the performance and results may be compared with ANN models (viz. MLP, RBF and Bayesian Network) with the same dataset.

ACKNOWLEDGEMENTS

One of the author (AKMF) gratefully acknowledges UGC and Ministry of Minority affairs for the award of Maulana Azad National Fellowship for the research work.

REFERENCES

[1] B. W. Melville, A. J. Sutherland, Design method for local scour at bridge piers,J. Hydraul. Eng., ASCE, vol. 114, No. 10, pp. 1210-1226, October 1988.

[2] D. S. Jeng, S. M. Bateni, E. Lockett, Neural network assessment for scour depth around bridge piers, Research Report No R855, Department of Civil Engineering, Environmental Fluids/Wind Group, The University of Sydney, November 2005.

[3] G. H. Macky, Survey of roading expenditure due to scour. CR 90_09, Department of Scientific and Industrial Research, Hydrology Centre, Christchurch, New Zealand, 1990.

[4] S. M. Bateni, S. M. Borghei, D. S. Jeng, Neural network and neuro-fuzzy assessment for scour depth around bridge piers, Eng. Appl. Artif. Intell., vol. 20, No. 3, pp. 401–414, April 2007.

[5] D.C. Froehlich, Local scour at bridge abutments. *Proc. Natl. Conf. Hydraulic Engineering* (New Orleans, LA: Am. Soc. Civil Eng.), pp. 13–18, 1989.

[6] J.K. Kandasamy, B.W. Melville, Maximum local scour depth at bridge piers and abutments, *J. Hydraul. Research*, 36(2), pp. 183-198, 1998.

[7] K.A. Kheireldin, "Neural Network Modeling for Clear Water Scour around Bridge Abutments". *J. Water Science*, 25(4), pp. 42-51, 1999.

[8] S.A. Begum, A.K. Md. Fujail, A.K. Barbhuiya, Radial Basis Function to predict scour depth around bridge abutment, IEEE Proceedings of the *2011 2nd National Conference on Emerging Trends and Applications in Computer Science*, (Shillong, Meghalaya, India), ISBN No. 978-1-4244-9581-8, pp. 76-82, 2011.

[9] S.A. Begum, A.K. Md. Fujail, A.K. Barbhuiya, Artificial Neural Network to Predict Equilibrium Local Scour Depth around Semicircular Bridge Abutments, *6thSASTech, Malaysia, Kuala Lumpur*, 2012.

[10] J. Koza, *Genetic programming: On the programming of computers by means of natural selection*, MIT Press, Cambridge, Mass, 1992.

[11] A. Guven, and M. Gunal, "Genetic programming approach for prediction of local scour downstream of hydraulic structures." *J. Irrig.Drain. Eng.*, 134(2), pp. 241–249, 2008.

[12] A. Guven and H. Md. Azamathulla and N. A. Zakaria. Linear genetic programming for prediction of circular pile scour. Ocean Engineering, 36(12-13), pp. 985-991, 2009

[13] H. Md. Azamathulla and A. Ab Ghani, N. A. Zakaria and A. Guven, Genetic Programming to Predict Bridge Pier Scour. Journal of Hydraulic Engineering, 136(3):165-169, 2010

[14] H. Md. Azamathulla, A. Guven and Y. K. Demir, Linear genetic programming to scour below submerged pipeline. Ocean Engineering, 38(8-9), pp. 995-1000, 2011.

[15] H. Md. Azamathulla, Gene expression programming for prediction of scour depth downstream of sills, Journal of Hydrology, 2012, In Press.

[16] S. Dey, A. K. Barbhuiya, Time Variation of Scour at Abutments, *Journal of Hydraulic Engineering*, 131(1), pp. 11-23, 2005.

APPENDIX A:

Author	Formula
Froehlich [5]	$\frac{d_{se}}{h} = 0.78 K_s K_\theta \left(\frac{l}{h}\right)^{0.63} F_r^{1.16} \left(\frac{h}{d}\right)^{0.43} \sigma_g^{-1.87} + 1$ Where, K_s=abutment shape factor, K_θ =abutment alignment factor, F_r=approaching flow Froude number, σ_g = geometric standard deviation
Kandasamy and Melville [6]	$d_{se} = K_s K_2 h^n l^{1-n}$ Where, K_s is the shape factor, K_2 = 5 and n = 1 for h/l <=0.04; K_2 = 1 and n = 0.5 for 0.04 < h/l < 1 and K_2 = 1 and n = 0 for h/l> 1