A prediction model for local scour depth based on BP and GA-BP neural network

Haiyang Dong¹, Lin Chong²*, Hanyu Zhou³, Zongyu Li³

¹ Ocean College, Zhejiang University, Hangzhou, Zhejiang Province, 310058, China
² College of Civil Engineering and Architecture, Zhejiang University, Hangzhou, Zhejiang Province, 310058, China
³ Ocean Research Center of Zhoushan, Zhejiang University, Zhoushan, Zhejiang Province, 316000, China

*Corresponding author’s e-mail: 11812073@zju.edu.cn

Abstract. A prediction model for the local scouring depth at bridge piers is built using BP and GA-BP neural network method. Measured data is collected from laboratory tests and field observation to work as train set of the predicting model which is verified by the measured data of Hangzhou Bay Bridge. The result shows that the predicted values of the local scour depth of the piers obtained by the two models are in good agreement with the measured values, which is more suitable than the existing general formula. What’s more, GA-BP model performs better than BP model.

1. Introduction
Local scour around piers can cause damage to the bridge and thus leading to bridge failure. According to a survey conducted by the U.S. Highway Administration in 1973, 75% of the 383 cases of bridge damage in the United States are related to pier damage [1]. In China, in 2010, pier base was exposed due to the flood, which directly led to the collapse of one pier Tongji Bridge in Huayang City, Sichuan Province. An accurate prediction of maximum scour depth at piles is essential for bridge safety.

There are three basic reasons for the local around piers:
1. Due to the reduction of the width of the section where the pier is located, the velocity and the energy per unit flow width are increased, resulting in the sediment movement.
2. The turbulence around the bridge pier is enhanced, causing erosion of sediment on the bed surface.
3. For the blocking effect of the pier, there forms a down-flow in front of piers that has an erosion effect on the bed surface at the front of the piers.

1.1 BP neural network
Artificial neural network (ANN) is an adaptive nonlinear dynamic system composed of a large number of neurons through extremely rich and perfect connections. ANN uses a large number of simply connected artificial neurons to imitate the characteristics of biological neural network, to obtain information from the external environment or other neurons, and to perform simple operations, and output the results to the external or other neurons associated with it. In this way, the neural network with specific structure can realize a mapping relationship.
Different neural network models are formed by different connection modes of neurons, among which the error back propagation network (BP neural network) is the most representative and widely used model at present. It is the simplest multilayer neural network, generally composed of three neuron layers, i.e. input layer, hidden layer and output layer.

1.2 GA-BP neural network
Genetic algorithms (GA) is an optimization method developed by imitating the evolution mechanism in nature. It is an efficient, parallel and adaptive global optimization search algorithm with random statistical theory based on Darwin's theory of biological evolution and Mendel's theory of heredity.

It uses simple coding technology to represent various complex problems, and carries out simple genetic operation for a group of codes, that is, according to the natural selection method of survival of the fittest to guide learning and determine the direction of search. The operation object of genetic algorithm is population, that is, a group of binary strings. Each population corresponds to a solution of the problem. The selected strategy of adaptation ratio is used to determine the fate of individuals in the population, while crossover and mutation are used to produce the next generation population. This mimics the evolution of life from generation to generation until the expected termination condition is met.

2. Prediction model setup
Han (2019) [2] conducted field observation in Zhejiang province, China (Jiashao Bridge, Hangzhou Bay Bridge, Jintang Bridge), in which a local scour depth predicting formula on basis of multiple linear regression was obtained.

Jian-Hao Hong (2016) [3] collected local scour depths of bridge in Taiwan Province in ‘A New Practical Method to Simulate Flood-Induced Bridge Pier Scour—A Case Study of Mingchu Bridge Piers on the Cho-Shui River’ during typhoons and floods.

In May 2012, the Federal Highway Administration of the United States included local scour depths at rivers and bridges in the U.S in a technical report ‘Pier Scour in Clear-Water Conditions with Non-Uniform Bed Materials’, where results of two sets of laboratory tests conducted from the J.Sterling Jones Water Conservancy Laboratory and the Colorado State University (CSU) were also listed [4]. Laboratory test results from Q. Liu (2017) [5], D.Max Sheppard (2006) [6], D.Max Sheppard (2004) [7], Subhasish Dey (1995) [8], Rui M. Lança (2013) [9], Simarro (2011) [10], Grimaldi (2005) [11], Lee(2009) [12] and Ettema(2006) [13] are also collected and used to train this predicting model in this paper.

Based on the results of bridge pier scouring listed above (3 field sets + 11 laboratory sets), 534 data sets in total, two more appropriate predicting models were obtained using BP and GA-BP algorithm.

3. Verification and discussion
The Hangzhou Bay Bridge, 36 kilometers in length, is the second longest cross-sea bridge in China.

Taking the observation local scour depth around piers in the Hangzhou Bay Bridge as an test sets, the prediction local scour models are verified. The flow velocity, median particle sediment diameter, pier width and water depth were used as the input parameters of the test group to obtain the prediction model.

BP model and GA-BP model were used to obtain predicted local scour depth of Hangzhou Bay Bridge, respectively. The comparison between the predicted scour depth and the measured value of the model is shown in Fig.1.
Figure 1. Comparison of measured scour depth and prediction from BP and GA-BP model

From Fig.1, there is only one BP neural network prediction result that lies beyond 50%; while all GA-BP model prediction are within 50% error, showing that this two prediction models have high accuracy. The neural network prediction model optimized by genetic algorithm is better than the standard BP model. Fig.2 shows the error distribution of the five formulas which are widely used in bridge engineering nowadays and this two neural network prediction model.

Figure 2. Error distribution of each prediction (Hangzhou Bay Bridge)
It can be seen from Fig.2 that the predicted value of GA-BP model and BP model is closer to the measured for the Hangzhou Bay sea crossing bridge, showing that those model perform better than predicting formulas exist.

In Fig.3, a=GA-BP model, b=BP model, c=65-1 formula, d=65-2 formula, e=HEC18 formula, f=M/S formula, g=B.W.M formula. Fig.3 shows the histogram of error distribution and cumulative frequency for all predicting results with field observations. From the perspective of the error concentration, the two prediction modes all perform well, while other formulas have large error distribution.

4. Conclusion
In this paper, a method based on neural network is used for predicting local scour depth around piers, which can meet the accuracy requirements after training. The models were verified by the measured data of the local scour depth at the piers of Hangzhou Bay Bridge, showing its effectiveness on local scour depth prediction. This two predicting models perform better than the existing prediction formulas. What’s more, GA-BP model works better than BP model.

Prediction accuracy of this neural network may be improved by introducing more field observation results and test results as train data set.

Acknowledgments
This research was financially supported by the Science and Technology Program Project of ZhouShan City of China(No.2020C41064).

References
[1] Wardhana, K., Fabian, C., Hadipriono, P.E. (2003) Analysis of Recent Bridge Failures in the United States. J. Journal of Performance of Constructed Facilities, 17(3): 144-150.
[2] Han, H., Chen, Y., Sun, Z. (2019) Estimation of Maximum Local Scour Depths at Multiple Piles of Sea/Bay-crossing Bridges. J. KSCE Journal of Civil Engineering, 23(2): p. 567-575.
[3] Hong, J.H., Guo, W.D., Cheiw, Y.M., et al. (2016) A New Practical Method to Simulate Flood-Induced Bridge Pier Scour—A Case Study of Mingchu Bridge Piers on the Cho-Shui River. J. Water, 8(6):p.238.
[4] Guo, J., Suaznabar, O., Shan, H., et al. (2012) Pier Scour in Clear-Water Conditions with Non-Uniform Bed Materials. Z.
[5] Liu, Q., Tang, H., Wang, H., et al. (2018) Critical velocities for local scour around twin piers in tandem. J. Journal of Hydrodynamics, 30(6): p. 1165-1173.
[6] Sheppard, D.M., Miller, W. (2006) Live-Bed Local Pier Scour Experiments. J. Journal of
Hydraulic Engineering, 132(7): p. 635-642.

[7] Sheppard, D.M., Odeh, M., Glasser, T. (2004) Large Scale Clear-Water Local Pier Scour Experiments. J. Journal of Hydraulic Engineering, 130(10): p. 957-963.

[8] Dey, S., Bose, S.K., Sastry, G.L.N. (1995) Clear Water Scour at Circular Piers: a Model. J. Journal of Hydraulic Engineering, 121(12): 869-876.

[9] Lança, R., Cristina, F., Rodrigo, M., et al. (2013) Clear-Water Scour at Pile Groups. J. Journal of Hydraulic Engineering, 139(10): 1089-1098.

[10] Simarro, G., Fael, C.M.S., Cardoso, A.H. (2011) Estimating equilibrium scour depth at cylindrical piers in experimental studies. J. Journal of Hydraulic Engineering, 137(9), 1089–1093.

[11] Grimaldi, C. (2005). Non-conventional countermeasures against local scouring at bridge piers. D. Universita’ della Calabria, Cosenza, Italy.

[12] Lee, S.O., Sturm, T.W. (2009) Effect of Sediment Size Scaling on Physical Modeling of Bridge Pier Scour. J. Journal of Hydraulic Engineering, 135(10): 793-802.

[13] Ettema, R., Gokhan, K., Marian, M. (2006) Similitude of Large-Scale Turbulence in Experiments on Local Scour at Cylinders. J. Journal of Hydraulic Engineering, 132(1):33-40.