A Prediction Model for Local Scour Depth around Piers Based on Machine Learning

Haiyang Dong\(^1\), Fanjun Chen\(^2\), Hanyu Zhou\(^3\), Cong Guo\(^4\), Zhilin Sun\(^1\)*

\(^1\) 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
\(^4\) Power China Huadong Engineering Corporation Limited, Hangzhou, Zhejiang Province, 310058, China

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

Abstract. A prediction model for the local scouring depth at bridge piers is built using machine learning. Measured data which is collected from laboratory tests and field observation is used to train the predicting model which is verified by the measured data of Hangzhou Bay Bridge. The result shows that the predicted value of the local scouring depth at piers obtained by the machine learning model is in good agreement with the measured ones, which is more suitable than existing general formula. The machine learning method is effective in predicting the local scour depth at bridge piers.

1. Introduction
The local scouring at bridge piers affects the safety of hydraulic structures such as bridges, docks and platform so seriously that this research is of great importance. This phenomenon is considered to be the main cause of bridge destruction, accounting for almost half of bridge collapses in the United States (K.Wardhana et al., 2003) [1]. Investigation and experimental research on the protection of bridge foundations are conducted by Academy of Railway Sciences of China from 1971 to 1974, showing that most of the damage on bridges was caused by severe flooding or insufficient burial depth of the bridge foundation.

Local erosion occurs near structures in rivers and seas with typical examples as erosion around bridge piers, abutments, spur dikes, and embankments. According to the flow continuity, when the cross-section area decreases, the flow velocity increases and the shear stress of the bed increases accordingly, resulting in river erosion. However, as the depth of the flow increases, the area of the flow increases, causing the erosion equilibrium. The shear stress of the river bed gradually reaches the critical value at that time.

There are many factors that affect the local erosion at the piers, such as the water flow factors including flow velocity, water depth, water density and viscosity coefficient; the sediment factors including particle size, gradation and bed sand density; the pile group factors such as bridge pier spaces and axis. Some of the predicting formulas are listed below.
With the development of computing and artificial intelligence technology, machine learning methods have been widely used in mathematical model building and disaster prediction. The core of machine learning is that the model analyzes massive amounts of data and mines the potential connections using mathematical algorithms in order to form an effective model for prediction.

In order to examine the accuracy of the simulation, data is divided into a training set and a test set according to a certain ratio (such as 8:2, 7:3). The training set refers to selection from the known data to simulate the curve while the test set is used to test the accuracy of the simulation curve. When fitting a model, it is necessary to rely on the data in the training set completely and use the test set to verify the accuracy.

2. Prediction model

Field observation was conducted by Han (2019) [2] in China (Jiahsao Bridge, Hangzhou Bay Bridge, Jintang Bridge), who obtained a local scour depth predicting formula using multiple linear regression. Jian-Hao Hong (2016) [3] collected local scour depths of Mingchu Bridge, Silo Bridge, Houfeng Bridge 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. Among them, Mingchu Bridge and Silo Bridge are built on Cho-Shui River, while Houfeng Bridge and Dachia Highway Bridge are built on Da-Chia River.

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’ on May 2012 [4]. Meanwhile, the results of two sets of laboratory tests conducted by the J. Sterling Jones Water Conservancy Laboratory in the Turner-Fairbank Highway Research Center (TFHRC) and the Colorado State University (CSU) were also listed. This paper also collected 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] and Grimaldi (2005) [11].

Based on the collected results of bridge pier scouring (3 field sets + 9 laboratory sets), 12 experimental sets and 440 data sets in total, a more appropriate predicting model is obtained using the linear regression method. The best suitable and highest accurate one was selected as the predicting model. When the input variable is an array of four variables, the multiple linear regression method is used for training and prediction.

\( x_j^{(i)} \) represents the training sample result value \( i \) of the input variable value \( j \).

\( x^{(i)} \) represents all input variable values of the training sample result value \( i \).

\( m \) represents the number of samples.

\( n \) represents the number of input variables.

The multiple linear regression model is [12]:

\[
h_{\theta}(x) = \theta_0 + \theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_n x_n
\]

The goal of linear regression is to find the most appropriate \( \theta_0, \theta_1 \) to make the model work best. The criterion for judging the accuracy of the model is called the Cost Function, among which the simplest one is the mean square error (MSE). \( P \) is represented as the cost function, whose definition is as follows [13]:

\[
P(\theta) = \frac{1}{2m} \sum_{i=1}^{m} (h_{\theta}(x^{(i)}) - y^{(i)})^2
\]

The most suitable parameter \( \theta \) is searched to minimize the cost function.

11 sets of field and test data were adopted in the local scour prediction model of the piers, which mainly focus on training with 4 sets of parameters including water depth, flow velocity, sediment size and pier width.
3. Verification

The Hangzhou Bay Bridge, starting from Haiyan, Jiaxing city and reaching Cixi, Ningbo city, is 36 kilometers in length and is the second longest cross-sea bridge in China. Taking the observation local scour depth of the piers in the Hangzhou Bay Bridge as an example, the prediction local scour model is verified. The flow velocity, median particle sediment diameter, pier width and water depth of the Hangzhou Bay Bridge were used as the input parameters of the test group to obtain the predicted results. Fig.1 shows the comparison between the predicted scour depth and the measured value of the model.

![Figure 1. Comparison of measured scour depth and prediction using machine learning](image1)

From the figure above, predicted local scour depths are in good agreement with the measured ones, with only one data point outside the 50% error line. It shows that the proposed machine learning method of predicting the local scour depth can effectively reflect the actual scour depth. Meanwhile, the correlation coefficient between the predicted value and measured value was calculated as 0.8376. Fig.2 shows the comparison of machine learning prediction models results and calculated results from other formulas.

![Figure 2. Comparison of measured scour depth and prediction of all formulas](image2)
From the above figure, the results of the machine learning model are represented by red color, and the results of other formulas are represented by light blue and green. The prediction performance of the machine learning model is better than other formulas.

The mean square error ($MSE$) between the predicted results and the measured ones is 5.89. The formula for calculating the mean square error ($MSE$) is:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (h_{\text{pre}} - h_{\text{obs}})^2$$

Obviously, the smaller the $MSE$, the more accurate the prediction model is. Meanwhile, the $MSE$ of the local scour depth prediction results and calculated results of other formulas are shown in Fig.4.

Among the prediction results of the Hangzhou Bay Bridge, the machine learning prediction result in this paper has the smallest MSE. It explained that the machine learning prediction model can better predict the local scour depth, which is better than the existing scour depth predicting formula.

Meanwhile, the mean absolute error MAE (Mean Absolute Error) of each formula is calculated. The calculation formula is as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{h_{\text{pre}} - h_{\text{obs}}}{h_{\text{obs}}} \right|$$

MAE represents the average absolute error of the prediction.
From the above figure, the absolute error of this model prediction result is the smallest, followed by 65-2 formula and the HEC-18 formula.

4. Factor Sensitivity Analyze

In the model established in this paper, there are four factors affecting the scour depth at the piers: flow velocity, water depth, sediment size and pier width. In order to obtain the influence of various variables on the results, the sensitivity analysis is conducted for each variable. The method is: a certain variable is removed before the machine learning model is re-established, which uses the model to predict the test samples to obtain the mean square error ($MSE$) and correlation coefficient. If $MSE$ is large and the correlation coefficient is small, the model is more sensitive to this factor. The analysis results are shown in the Table 1 and Fig.6.

| Model                        | $MSE$ | Correlation Coefficient $R$ |
|------------------------------|-------|-----------------------------|
| all variables included       | 5.87  | 0.84                        |
| lacking median sediment size ($d_{50}$) | 8.75  | 0.79                        |
| lacking pier width (D)       | 13.71 | 0.56                        |
| lacking flow velocity (V)    | 13.90 | 0.70                        |
| lacking water depth(H)       | 7.55  | 0.82                        |

Figure 5. Mean square error and R for models lacking factors

It can be seen from the table and the figure that when the pier width D is lacking, the $MSE$ of the prediction model result obtained is the large, and the correlation coefficient between the measured value and the predicted value is the smallest, showing that the pier diameter has the greatest influence on the scouring depth. According to the analyze results in this paper, the importance of the various factors is ranked as follows: the pier diameter, the flow velocity, the median sediment size and the water depth.

5. Conclusion

The existing predicting formulas of the local scour depth around piers are mostly semi-empirical and semi-theoretical formulas based on theoretical analysis and dimensional analysis.

In this paper, a method based on machine learning is proposed to predict the local scour depth of piers, which can meet the accuracy requirements after training. The model is verified by the measured data of the local scour depth at the piers of Hangzhou Bay Bridge, showing its effectiveness on
predicting the local scour depth around bridge piers. This predicting model performs better than the existing prediction formulas. More field observation results and test results can be introduced into this machine learning prediction model to improve the accuracy.

Acknowledgments
This work was 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, 139(7), 1089–1093.
[11] Grimaldi, C. (2005). Non-conventional countermeasures against local scouring at bridge piers. D. Universita’ della Calabria, Cosenza, Italy.
[12] Gao, Y.Y., Sun, Z.L. (2014) Wake flow behavior behind a smaller cylinder oscillating in the wake of an upstream stationary cylinder. J. Fluid Dynamics Research, 46(2).
[13] Muzzammil, M., Alama, J., Danish, M. (2015) Scour Prediction at Bridge Piers in Cohesive Bed Using Gene Expression Programming. J. Aquatic Procedia, 4: 789-796.