International Journal of Architectural, Civil and Construction Sciences
ISSN: 2415-1734
Vol:11, No:6, 2017

Scour Depth Prediction around Bridge Piers Using Neuro-Fuzzy and Neural Network Approaches

H. Bonakdari, I. Ebtehaj

***Abstract*—**The prediction of scour depth around bridge piers is frequently considered in river engineering. One of the key aspects in efficient and optimum bridge structure design is considered to be scour depth estimation around bridge piers. In this study, scour depth around bridge piers is estimated using two methods, namely the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Network (ANN). Therefore, the effective parameters in scour depth prediction are determined using the ANN and ANFIS methods via dimensional analysis, and subsequently, the parameters are predicted. In the current study, the methods' performances are compared with the nonlinear regression (NLR) method. The results show that both methods presented in this study outperform existing methods. Moreover, using the ratio of pier length to flow depth, ratio of median diameter of particles to flow depth, ratio of pier width to flow depth, the Froude number and standard deviation of bed grain size parameters leads to optimal performance in scour depth estimation.

***Keywords*—**Adaptive neuro-fuzzy inference system, ANFIS, artificial neural network, ANN, bridge pier, scour depth, nonlinear regression, NLR.

I. Introduction

BRIDGES are the most important and applicable river structures. Every year, with river flood events, a large number of bridges are destroyed. In addition to loss of life, bridge destruction directly and indirectly imposes vast costs worldwide. One of the most influential factors on bridge destruction is local scour around bridge piers. Scour causes holes around bridge piers and undermines bridge stability and perhaps with great floods, it could lead to destruction. Dealing water flow to bridge piers and flow separation from piers are known as the main local scour factors. As water deal to a bridge pier due to the pressure decrease from the free flow surface to the bed, a downward flow is created. These flows are in contact with the bed at the beginning and then at the mainstream they create a horseshoe vortex. These vortices are mostly active in front of the pier. Flow separation from the bridge pier behind the vortex base increases. The reason for higher vortex formation is the increase in shear stress behind the bridge pier. Studies have shown that horseshoe vortices have a major role in scour formation around bridge piers [1]. Numerous studies were conducted to evaluate the horseshoe vortices characteristics and their effects on the pier width [2], [3].

Until now, many researchers have studied bridge pier scour. However, due to the complexity of the three-dimensional and three-phase flow (air, water and sediment) and major factors on the phenomenon, providing a unique solution for scour depth calculation or reduction has still not been successful [4]-[6]. Factors such as sediment, bridge geometry, flow, and sediment characteristics can be considered the most important factors affecting scour depth. Thus, due to the significant parameters and the absence of a clear procedure with good accuracy, there is a need for a method that overcomes the problems posed by existing methods.

In recent years, artificial intelligence methods have been effective and strong techniques to solve the non-linear and complex issues in various fields including water and hydraulic engineering [7]-[12]. Neural networks can be good and effective methods to overcome the linear and NLR -based method problems with scour [13]-[15]. ANFIS using ANN features can approximate Fuzzy Inference Systems (FIS). In fact, this method, which is a combination of ANN and FIS, has demonstrated good performance in hydraulic modelling and environmental aspects [16]-[18].

The main objective of this study is to use ANFIS to predict scour depth around bridge piers. The factors affecting scour depth are first determined, after which dimensional analysis is applied to determine the dimensionless parameters for modeling. Moreover, sensitivity analysis is employed to evaluate the effect of each dimensionless parameter on scour depth modeling using ANFIS. The ANFIS results are compared with ANN and NLR method results.

II. Artificial Neural Network

ANN is among the computational models capable of mapping the input and output of a system. However, the determination of complex and nonlinear systems by a network of nodes are connected together. ANN architecture usually consists of three layers: "input layer", which communicates to one or more "hidden layers" where the actual processing is done via a system of weighted connections. The hidden layers then link to an "output layer" where the answer is output. It is worth noting that there can be different hidden layers, but previous studies have shown that one hidden layer can estimate a complex and non-linear function [19]-[21]. The neural network used in this study is a Feed-Forward Neural Network (FFNN), whose output can be expressed as:

Hossein Bonakdari is with the Department of civil engineering, Razi University, Kermanshah, Iran (e-mail: bonakdari@ yahoo.com).
Isa Ebtehaj is with the Department of civil engineering, Razi University, Kermanshah, Iran (e-mail: isa.ebtehaj@gmail.com).

$$a = f\left(\sum_{i=1}^{n} p_i w_{j,i} + b_j\right) \quad (1)$$

where p_i is the output of neuron M_i, $w_{j,i}$ is the connection weight between the neurons of the current layer (M_j) and the previous layer (M_i), b_j is the bias weight of neuron M_j and f is the nonlinear transfer function. Regarding the good performance of the sigmoid transfer function in recent studies [15], [22], this activation function is used in the current study and is defined as follows:

$$f(x) = \frac{1}{1 + exp(-x)} \quad (2)$$

The target function determined for ANN training is defined as follows:

$$f(w) = \frac{1}{M}\sum_{k=1}^{M}(y_k^{actual} - y_k^{predict})^2 \quad (3)$$

where y_k^{actual} and $y_k^{predict}$ are the actual and predicted output (respectively). To train the neural network, a back-propagation (BP) algorithm is used. This algorithm returns the calculated error from the output layer to the hidden layer and then the input layer as well.

III. Adaptive Neuro-Fuzzy Inference System (ANFIS)

The FIS recognizes IF-Then rules so that the interaction between the number of input and output variables can be obtained. The system can be used as a predictive model for a condition in which the input or output data has high uncertainty. The fuzzy modeling process concludes the membership function determination by determining the inference system based on the data, writing the inference rules and rule combinations, obtaining the results and finally, defuzzification. To mitigate this uncertainty problem, Jang [23] proposed one of the most common neuro-fuzzy hybrid models, ANFIS. This model implements the Sugeno model system in a neural structure and sets the membership functions through the back-propagation (BP) algorithm or a hybrid of BP and least squares. Considering an ANFIS model with two inputs x and y and one output z, the If-Then rules can be stated as follows:

$$Rule1: if \ \ x \ is \ A_1 \ \ and \ \ y \ is \ B_1, \ \ Then \ \ f_1 = p_1 x + q_1 y + r_1 \quad (4)$$

$$Rule2: if \ \ x \ is \ A_2 \ \ and \ \ y \ is \ B_2, \ \ Then \ \ f_2 = p_2 x + q_2 y + r_2 \quad (5)$$

where A_1, A_2, B_1 and B_2 are membership functions of the x and y inputs and p_1, q_1, r_1, p_2, q_2 and r_2 are the parameters of the output functions. The ANFIS model contains 5 different layers, which can be defined as follows:

First layer: each node in this layer indicates the input parameter membership degree as follows:

$$o_{i,1} = \mu A_i(x), \qquad i = 1,2 \quad (6)$$

$$o_{i,1} = \mu B_{i-2}(y), \qquad i = 3,4 \quad (7)$$

where x and y are the inputs of node i; A_i and B_{i-2} are the fuzzy set of node i, and $O_{1,i}$ is the membership degree of the fuzzy set. As the Gaussian function has the advantages of being smooth and nonzero and also has fewer parameters than other membership functions, such as the bell and trapezoidal functions, in this study the function defined below is used.

$$\mu_{A_i(x)} = \exp\left(-\frac{\|x - c_i\|^2}{2\sigma_i^2}\right) \quad (8)$$

where c_i and σ_i are the parameter set which is between 0 and 1.
Second layer: in this layer, the membership degree of each rule is calculated as follows:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(x) \qquad i = 1,2 \quad (9)$$

Third layer: in this layer, the input data is processed as follows:

$$O_{3,i} = \overline{w}_i = \frac{w_1}{w_1 + w_2}, \qquad i = 1,2 \quad (10)$$

Fourth layer: in this layer, each node's output is calculated as follows:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \quad (11)$$

The fifth layer: in this layer, all nodes are summed and the total output is calculated as follows:

$$O_{5,1} = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \quad (12)$$

In this study, for FIS generation and model training, grid partitioning and a hybrid of back-propagation and least squares algorithm are used, respectively.

IV. Data presentation for Scour depth PREDICTION

Scour depth around bridge piers (d_s) for equilibrium state and when there is constant flow on the bed with uniform and no cohesive sediments, is related to different variables. The variables dependent on scour depth include sediment characteristics, fluid, flow and pier specifications. Thus, the variables dependent on local scour depth (d_s) estimation can be expressed as the following function:

$$d_s = f(g, d_{50}, b, y, L, V, \sigma) \quad (13)$$

where g is the gravitational acceleration, d_{50} is the median diameter of particles, b is the pier width, y is the flow depth, L

is the pier length, V is the mean approach velocity and σ is the standard deviation of grain size distribution. Using dimensional analysis and the Π Buckingham theory, the dimensionless parameters affecting local scour depth estimation are provided as follows:

$$d_s / y = f(Fr, d_{50} / y, b / y, L / y, \sigma) \quad (14)$$

where Fr is the Froude number.

The parameters given in the above relationship and field data are used to develop ANN and ANFIS models. For ANN and ANFIS modeling, 467 different field data collected by Landers and Mueller [24] and Mohammed et al. [25] are used. These data are related to 4 pier shapes, including cylindrical, round, square and sharp. Among all data, by using random selection, 25% (117 data) were selected and the remaining 75% served to train the ANN and ANFIS models. The data ranges used in this study are as follows: $0.027<Fr<0.816$; $2.25E\text{-}5<d_{50}/y<0.144$; $0<L/y<110$; $1.2<\sigma<20.3$; $0.025<d_s/y<3.33$

V. Results and Discussion

In this section, the local scour depth results are expressed using ANFIS and compared with the ANN and NLR results. For this purpose, three different statistical indices, viz root mean squared error (RMSE), mean absolute relative error (MARE) and BIAS are used.

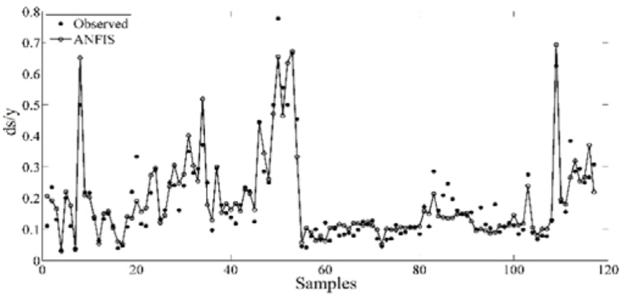
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left((d_s/y)_{Observed\,i} - (d_s/y)_{Model\,i}\right)^2} \quad (15)$$

$$MARE = \sum_{i=1}^{n}\left(\frac{(d_s/y)_{Observed\,i} - (d_s/y)_{Model\,i}}{(d_s/y)_{Observed\,i}}\right) \quad (16)$$

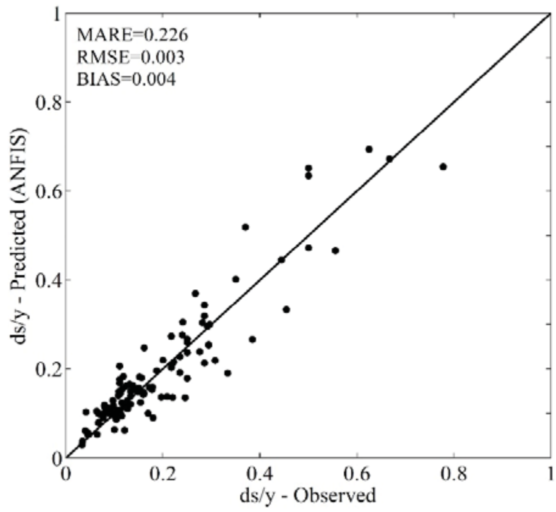
$$BIAS = \sum_{i=1}^{n}\left((d_s/y)_{Model\,i} - (d_s/y)_{Observed\,i}\right) \quad (17)$$

Fig. 1 presents the performance of ANFIS in local scour depth prediction. This figure indicates that most of the values estimated by ANFIS are accurate and the model performance for almost all d_s/y is constant. By increasing or decreasing this parameter, no significant change is observed in ANFIS d_s/y prediction performance. An evaluation of quantitative model performance also signifies good accuracy (MARE = 0.226; RMSE = 0.003). The BIAS index also shows that these models performed with overestimation. The index (BIAS = 0.004) has a negligible value, which has no significant impact on a plan's economic viability.

Table I represents an evaluation of the effect of each input parameter on ANFIS model prediction of local scour depth. Not using the standard deviation of the bed grain size (σ) parameter led to a significant reduction in local scour depth prediction accuracy using ANFIS, as all three index values presented significantly increased.



(a)



(b)

Fig. 1 ANFIS model performance evaluation for local scour depth prediction: a)series data b) scatter plot

The average relative error (MARE) value increased by approximately 5 times, which is correct for the RMSE model, and the RMSE value increased by about 6 times for ANFIS (2) compared to ANFIS (1). The estimation process by ANFIS (2) compared to ANFIS (1) was unchanged and both models performed with overestimation, whereby the BIAS (0.085) value for ANFIS (2) was significantly different from ANFIS (1). ANFIS (3) outperformed ANFIS (2), but the model results indicate that not using dimensionless parameter L/y as a model input can lead to a significant reduction in local scour depth prediction accuracy. The average relative error and root mean square error were respectively 2 and 4 times the values provided for these indices for the ANFIS (1) model (MARE = 0.549; RMSE = 0.019). This model performed with underestimation, but due to the low BIAS (-0.003) index value, this process did not cause problems. The ANFIS (4) model only considers four parameters Fr, d_{50} / y, L / y *and* σ among five dimensionless parameters provided in (14) as effective parameters in local scour depth determination. This model's accuracy is similar to the ANFIS (3) model and their statistical index values are not significantly different from each other. In fact, not using of one of parameters l/y or b/y as effective parameters leads to relatively similar results, with the difference being that ANFIS

(3) performed with underestimation and ANFIS (4) with overestimation. Not using parameters d_{50}/y (ANFIS (5) and Fr (ANFIS (6)), which are sediment and flow characteristics respectively, led to reduced model accuracy. Moreover, the average relative error value was about 3 times that of ANFIS (1) in which all parameters provided in (14) are considered effective parameters. The RMSE index value for ANFIS (5) (RMSE = 0.215) is almost three times higher than for ANFIS (6). This suggests that for higher and lower d_s/y values, ANFIS (6) and ANFIS (5) performed better, respectively. According to this explanation, not using each of the variables presented in (14) led to significant accuracy reduction in local scour depth prediction using ANFIS.

ANFIS (1): $d_s / y = f(Fr, d_{50} / y, b / y, L / y, \sigma)$

ANFIS (2): $d_s / y = f(Fr, d_{50} / y, b / y, L / y)$

ANFIS (3): $d_s / y = f(Fr, d_{50} / y, b / y, \sigma)$

ANFIS (4): $d_s / y = f(Fr, d_{50} / y, L / y, \sigma)$

ANFIS (5): $d_s / y = f(Fr, b / y, L / y, \sigma)$

ANFIS (6): $d_s / y = f(d_{50} / y, b / y, L / y, \sigma)$

TABLE I
INPUT PARAMETER SENSITIVITY ANALYSIS FOR THE ANFIS MODELS

Model	MARE	RMSE	BIAS
ANFIS (1)	0.226	0.003	0.004
ANFIS (2)	1.163	0.019	0.085
ANFIS (3)	0.549	0.012	-0.003
ANFIS (4)	0.513	0.069	0.036
ANFIS (5)	0.627	0.215	0.062
ANFIS (6)	0.652	0.076	0.050

Due to the necessity to use all five parameters $Fr,\ d_{50} / y,\ b / y,\ L / y\ and\ \sigma$, it is recommended to use NLR in the following equation to calculate scour depth. Fig. 2 compares the ANFIS, ANN and NLR models in terms of local scour depth estimation. The ANN models' relative error was overestimated, but with increasing the d_s/y value, the model performance changed to underestimation. ANFIS (MARE = 0.226; RMSE = 0.003; BIAS = 0.004) displayed better performance in nearly all data ranges than ANN (MARE = 0.694; RMSE = 0.016; BIAS = 0.034). Both models performed with overestimation, with a wide difference between the BIAS index values of ANN and ANFIS. NLR (MARE = 0.777; RMSE = 0.016; BIAS = 0.038) estimated local scour depth for almost all data ranges with large relative error in both underestimation and overestimation. A quantitative comparison of this model with two artificial intelligence methods (ANN and ANFIS) showed that both artificial intelligence methods outperformed the NLR model. Hence, it can be concluded that that the ANFIS method presented in this study was more accurate in d_s/y estimation compared to the NLR and ANN methods that are based on regression and artificial intelligence.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left((d_s/y)_{Observed\,i} - (d_s/y)_{Model\,i}\right)^2} \qquad (18)$$

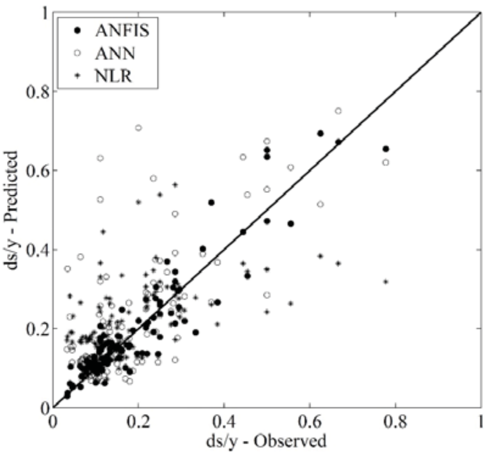


Fig. 2 Comparison of ANFIS, ANN and NLR in local scour depth prediction

TABLE II
PERFORMANCE EVALUATION OF ANFIS, ANN AND NLR IN LOCAL SCOUR DEPTH PREDICTION

Method	MARE	RMSE	BIAS
ANFIS	0.226	0.003	0.004
ANN	0.694	0.016	0.034
NLR	0.777	0.016	0.038

VI. CONCLUSION

Since one of the major reasons for bridge failure is local scour depth, accurate scour depth prediction is essential and inevitable. Therefore, the ANFIS and a large range of field data were used in this study to predict scour depth around bridge piers. Thus, by recognizing the effective parameters on scour depth and using dimensional analysis to introduce the dimensionless parameters, 5 different parameters were introduced, including Froude number (*Fr*), ratio of median diameter of particles to flow depth (d_{50}/y), ratio of pier width to flow depth (b/y), ratio of pier length to flow depth (L/y) and standard deviation of grain size distribution (σ). Scour depth modeling indicated the relatively good performance of ANFIS (MARE = 0.226; RMSE = 0.003; BIAS = 0.004). Also, the effect of each dimensionless parameter on scour depth modeling using ANFIS showed that not using any of the parameters provided in (14) leads to significant reduction in ANFIS performance. Not using the σ parameter in the ANFIS (2) model (MARE = 1.163; RMSE = 0.019; BIAS = 0.085) resulted in the greatest reduction in ANFIS performance and not using parameter b/y in the ANFIS (4) model (MARE = 0.513; RMSE = 0.069; BIAS = 0.036) resulted in minimum ANFIS performance reduction. A comparison of ANFIS results with ANN as an artificial intelligence method based on NLR showed that the method proposed in this study performed the best.

REFERENCES

[1] N. H. C. Breusers, A. J. Raudkivi, "Scouring," 2nd hydraulic structures design manual, Balkema, Rotterdam, The Netherlands, 1991

[2] S. Das, R. Das, A. Mazumdar, "Circulation characteristics of horseshoe vortex in scour region around circular piers," *Water Sci. Eng.,* vol. 6, no. 1, pp. 59-77, 2013.

[3] S. Das, A. Mazumdar, "Comparison of Kinematics of Horseshoe Vortex at a Flat Plate and Different Shaped Piers," *Int. J. Fluid Mech. Res.*, vol. 42, no. 5, 2015.

[4] E. M. Laursen, A. Toch, "Scour Around Bridge Piers and Abutments," *Iowa Highway Research Board*, Ames, IA, USA, Bulletin 4, 1956.

[5] B. V. Melville, A. J. Sutherland, "Design method for local scour at bridge piers," *J. Hydraul. Eng*., vol. 114, no. 10, pp. 1210–1226, 1998.

[6] E. V. Richardson, S. R. Davis, "Evaluating Scour at Bridges," *Hydraulic Engineering Circular No. 18 (HEC-18)*, US Department of Transportation, Federal Highway, 2001.

[7] I. Ebtehaj, H. Bonakdari, F. Khoshbin, H. Azimi, "Pareto Genetic Design of GMDH-type Neural Network for Predict Discharge Coefficient in Rectangular Side Orifices," *Flow Meas. Instrum.,*. vol. 41, pp. 67-74. 2015.

[8] I. Ebtehaj, H. Bonakdari, A. H. Zaji, H. Azimi, F. Khoshbin, "GMDH-type neural network approach for modeling the discharge coefficient of rectangular sharp-crested side weirs," *Eng. Sci. Technol. Int. J*., vol. 18, no. 4, pp. 746-757, 2015.

[9] F. Khoshbin, H. Bonakdari, S. H. Ashraf Talesh, I. Ebtehaj, A. H. Zaji, H. Azimi, "Adaptive neuro-fuzzy inference system multi-objective optimization using the genetic algorithm/singular value decomposition method for modelling the discharge coefficient in rectangular sharp-crested side weirs," *Eng. Optimiz*., vol. 48, no. 6, pp. 933-948, 2015

[10] M. Najafzadeh, Gh-A. Barani, M. R. Hessami-Kermani, "Abutment scour in live-bed and clear-water using GMDH Network," *Water Sci. Technol.,* vol. 67, no. 5, pp. 1121-1128, 2013.

[11] M. Najafzadeh, G. A. Barani, H. M. Azamathulla, "Prediction of pipeline scour depth in clear-water and live-bed conditions using group method of data handling," *Neural Comput. Appli.*, vol. 24, no. 3-4, pp. 629-635, 2014.

[12] M. Najafzadeh, A. Zahiri, "Neuro-Fuzzy GMDH-Based Evolutionary Algorithms to Predict Flow Discharge in Straight Compound Channels," *J. Hydrol Eng.*, 04015035, 2015.

[13] A. R. Kambekar, M. C. Deo, "Estimation of Pile Group Scour Using Neural Networks," Appl. Ocean Res., vol. 25, no. 4, pp. 225-234, 2003.

[14] S. U. Choi, S. Cheong, "Prediction of local scour around bridge piers using artificial neural networks," *J. American Water Resour. As*soc., vol. 42, no. 2, pp. 487-494, 2006

[15] I. Ebtehaj, H. Bonakdari, "Evaluation of Sediment Transport in Sewer using Artificial Neural Network," *Eng. Appl. Comput. Fluid Mech.,* vol. 7, no. 3, pp. 382–392.

[16] O. F. Dursun, N. Kaya, M. Firat, "Estimating discharge coefficient of semi-elliptical side weir using ANFIS," *J. Hydrol.*, vol. 426, pp. 55-62, 2012.

[17] F. Salmasi, M. Özger, "Neuro-Fuzzy Approach for Estimating Energy Dissipation in Skimming Flow over Stepped Spillways," *Arab. J. Sci. Eng.*, vol. 39, no. 8, pp. 6099-6108, 2014.

[18] I. Ebtehaj, H. Bonakdari, "Performance Evaluation of Adaptive Neural Fuzzy Inference System for Sediment Transport in Sewers," *Water Resour. Manage.,* vol. 28, no. 13, pp. 4765–4779, 2014.

[19] K. Hornik, M. Stinchcombe, H. White, "Multilayer feedforward networks are universal approximators," *Neural networks*, vol. 2, no. 5, pp. 359-366, 1989.

[20] Z. F. Liu, X. P. Liu, S. W. Wang, G. F. Liu, "Recycling strategy and a recyclability assessment model based on an artificial neural network," *J. mater. Process. Tech.*, vol. 129, no. 1, pp. 500-506, 2002.

[21] M. Gupta, L. Jin, N. Homma, "Static and dynamic neural networks: from fundamentals to advanced theory," John Wiley & Sons, 2004.

[22] I. Ebtehaj, H. Bonakdari, "Assessment of evolutionary algorithms in predicting non-deposition sediment transport. *Urban Water J*., vol. 3, no. 5, pp. 499-510, 2016.

[23] J. S. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE Trans Syst Manage Cyb*., vol. 23, no. 3, pp. 665–685, 1993.

[24] M. N. Landers, D. S. Mueller, "U.S. Geological survey field measurements of pier scour," *Proce. Compendium of papers on ASCE water resources engineering conference 1991 to 1998*, pp. 585-607, 1999.

[25] T. H. Mohammed, M. J. M. M. Noor, A. H. Ghazali, B. B. K. Huat, "Validation of some bridge pier scour formulate using field and laboratory data." *Am. J. Environ. Sci*., vol. 1, no. 2, pp. 119-125, 2005.