Artificial Neural Network Modeling to Predict Complex Bridge Pier Scour Depth

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Abstract
Flow mechanism around a bridge pier is complicated and difficult to present a general model to provide a good prediction of scour depth. Geotechnical and economical parameters govern design of complex bridge pier design. The interaction between flow parameters and complex bridge pier is necessary to study to accurately predict the performance of system. In this study, an artificial neural network (ANN) has been developed to predict scour depth around complex bridge pier. ANN model, feed forward back propagation, FFBP, was utilized to estimate the depth of scour hole. 82 experiments have been carried out to collect experimental data. The training and testing experimental data on local scour depth around complex piers are selected from several references. Three categories of input data were used for network training: the first input combination includes cases that pile cap was above the original bed; the second combinations refers to semi buried pile cap, both combinations contains 15 dimensional parameters; and the third combination consists of cases that pile cap was below the original bed level which contains 8 dimensional parameters. ANN results have been compared with the results of empirical methods. Sensitivity analysis showed that pile spacing width, longitudinal extension of pile group from column, and column length have the least influence on scour depth. While the number of piles in line with flow, transversal extension of pile cap from column, and pile cap length are the most effective parameters on complex pier scour in each combination respectively. Based upon an errors and sensitivity analyses it may be said, the collected data and method of analysis could be reliable to use.

Keywords: Scour depth; Complex piers; Neural network; Sensitivity analysis.

Introduction

When a stream cross section is partially obstructed by a bridge pier, flow pattern around the pier changes significantly. Bridge pier produces an adverse pressure gradient just upstream. Besides, pier upstream boundary layer undergoes a three-dimensional separation. Shear stress distribution around the pier drastically changes due to formation of a horseshoe vortex, resulting in a scour formation hole around the pier, which in turn, changes flow pattern and shear stress (Kothyari et al. 1992). Furthermore, a precise estimation of maximum scour depth around bridge pier is necessary. Due to the geotechnical and economic reasons, complex bridge pier have become popular. However, scour prediction is necessary for this kind of pier (Zounemat et al., 2009). Few empirical methods have been proposed to estimate maximum scour depth around complex piers under clear-water condition [HEC-18 (Richardson and Davis 2001), Sheppard and Glasser (2004), and Coleman (2005). The main problem of these methods is that they are based on dimensional analysis and data correlation of experimental studies that do not always produce reasonable results for field conditions or even for laboratory conditions. Therefore, they may mostly give conservative results and overestimate the scour depth. Artificial neural networks (ANNs) are interconnected nodes or neurons that can be used as a heuristic approach for solving complex problems. ANNs can be trained to learn the unknown relationship between two sets of input and output data. A multiplayer perceptron (MLP) is used to train the network. It seems MLP may produce a good model in mathematical problem. A common MLP network consists of input, hidden and output layers. Each layer of a network includes a number of known independent and dependent parameters, respectively. However, the number of hidden neurons depends on the complexity of the problem and is determined during the training process by trial and error (Demuth et al. 2009). Many applications of ANNs have been successfully conducted on bridge pier scour. Kambekar (2003) investigated an ANNs to predict scour depth at pile group. He used the back-propagation algorithm to modify the Jordan-Elman scheme in order to recurrent network for estimation of pile group scour depth. Lee et al. (2007) used back-propagation-network to predict the scour depth around bridge piers. Bateni et al. (2007) developed artificial neural network and adaptive neuro-fuzzy inference system (ANFIS) models for equilibrium and time-dependent scour depth prediction around bridge piers. Zounemat et al. (2009) investigated the potential of two types of neural networks, feed forward back propagation and radial basis function accompanied by an adaptive neuro-fuzzy inference system, for local scour depth at pile groups under steady, clear-water scour conditions in uniform sediments. Kaya (2010) considered artificial neural network to evaluate the scour depth around bridge piers. Ismail et al. (2013) considered a feed forward neural network with an adaptive activation function to prediction bridge pier scour depth. The main objective of this study was to investigate the effects of complex bridge pier geometric parameters on equilibrium scour depth. For this purpose, experiments were performed to effect the different geometric parameters on scour depth. These data were added to previous data to evaluate the artificial neural network accuracy to predict the local scour depth around complex bridge piers. Some attempts were made to determine the optimum network structure. In addition, predicted results obtained from the optimized ANN model were compared with the experimental data.

Model Development

The dimensional analysis presented in this paper will be used to discuss the effect of geometric parameters on the scour depth around complex. For complex piers, a functional relationship for maximum scour depth can be expressed as:

$$y_s = f(D_c, L_c, D_{pc}, L_{pc}, T, Y, f_{cu}, f_{cs}, D_p, S_m, S_n, m, n, f_{cu\,pg}, f_{cs\,pg}) \quad (1)$$

In which D_c=column width, D_{pc}=pile cap width, T=pile cap thickness, f_{cu} and f_{cs}=upstream and side extensions of the pile cap with respect to the column, respectively, D_p=pile diameter, m=number of piles in line with the flow, n=number of piles normal to the flow, S_m= pile spacing in the flow direction, and S_n= pile spacing normal to flow. When pile cap is above the initial bed level and for a semi buried pile cap, all of the geometric parameters of complex pier may be influenced on scour process. Hence, functional relationship for maximum scour depth can be expressed as Eq. (1). In addition, while pile cap is below the initial bed level, maximum scour depth presented as:

$$y_s = f(D_c, L_c, D_{pc}, L_{pc}, T_{pc}, Y_{pc}, f_{cu}, f_{cs}) \quad (2)$$

Three combinations of input data were used for network training: the first and second input combinations contain fifteen variables, which are column width, column length, pile cap width, pile cap length, pile cap thickness, pile cap elevation, upstream and side extensions of pile cap width respect to column, pile diameter, pile spacing in the flow direction, pile spacing normal to the flow, number of piles in line with the flow, number of piles normal to the flow, and longitudinal and transversal extension of pile group from column, respectively, which are called cases I and II. The third input combination contains eight variables, which are column width, column length, pile cap width, pile cap length, pile cap thickness, pile cap elevation, and upstream and side extensions of pile cap with respect to column, which is called case III.
The first input combination, case I, which is consisted of 135 data sets, refers to the position that pile cap was above the initial bed level. The second input combination, case II, which is consisted of 216 data sets, refers to the position that pile cap was semi buried. And, the third input combination, case III, which is consisted of 125 data sets, refers to the position that pile cap was completely buried.

ANN model

The performance of artificial neural network (ANN) configuration was assessed based on calculating the mean absolute error (MAE) and the root mean square error (RMSE). The coefficient of determination, R^2, of linear regression line between the predicted values from either the ANN and the desired output was also used as a measure of performance. The three statistical parameters used to compare the performance of the various ANN configurations.
Both of input and output variables were first normalized by two approaches by means of Eqs. (6) and (7):

$$I_N = \frac{I - I_{\min}}{I_{\max} - I_{\min}} \quad (3)$$

$$I_M = \frac{I - \bar{I}}{\sigma} \quad (4)$$

Where I_N and I_M are normalized value of I, I_{max} and I_{min} respect the maximum and minimum value of each variable of original data, respectively, $\bar{I}$ is the average of data and σ stands for data standard deviation. Eq. (3) makes data within an average of 0 and variance of 1. The hyperbolic tangent sigmoid (tansing) transfer function with a back-propagation algorithm at the hidden layer and a linear transfer function (purelin) at the output layer were applied. In the next step, the data sets were divided into different sets: a training dataset with one-half of the data for training the ANN; a validation dataset with one-quarter of the data for validating the developed ANN; and a testing set with one-quarter of the data for testing the ANN. The division of the datasets was followed by performing various learning algorithms to select the best one.
In order to select the best back propagation learning algorithm, different types of learning algorithm were performed. A three layer feed forward ANN with a tansing transfer function at the output layer was used for all the back propagation learning algorithms. The number of hidden layer neurons is an essential parameter affecting the performance of ANNs. If the value is set too low, the network would not be trained properly, and if it is too high, the network would be over trained. In this study, the best number of neurons in the hidden layer was determined by the trial and error method in which the number of neurons was varied from 2 to 20. The minimum value of 0.077828, 0.13115, and 0.073049 are calculated for 10, 14, and 8 neurons in hidden layer for cases I, II, and III, respectively. Therefore, the ANN was designed with 10, 14, and 8 neurons in the hidden layer.

Results and discussion

As it was mentioned earlier, a three layer FFBP-NN with 10, 14, and 8 neurons for cases I, II, and III, respectively, was considered as the executive model. To assess the performance of the models, observed scour depth values are plotted against the predicted ones. Figs. 1-3 compare the observed and predicted values for the training and testing data when FFBP-NN is trained for case I, II, and III, respectively.
To evaluate the accuracy and capability of the applied models in estimating scour depth, comparison between the new models and five of the existing procedures was undertaken.

A comparison of the ANN with the empirical models is shown in Fig. 4, for different values of pile cap elevations. The results show that the neural network proposed in this study is more accurate than the traditional regression based methods.

Sensitivity analysis

Sensitivity analysis has been conducted to assess the extent to which the model depends on each of input parameters. The analysis is carried out in turns, with one of the parameters taken away from the input vector in each turn and the performance of the model is evaluated until all parameters are covered. Based upon the MAE, RMSE, and R, it could be concluded that pile spacing width, S_n, and longitudinal extension of pile group from column, $f_{cu\ pg}$, and column length, L_c, have the least influence on scour depth for cases I, II, and III, respectively. While the number of piles in line with flow, m, and transversal extension of pile cap from column, f_{cs}, and pile cap length, L_{pc}, are the most effective parameters on complex pier scour depth for cases I, II, and III, respectively.

Conclusions

This study investigated the effects of geometric parameters on complex bridge pier scour depth. Some experiments were conducted to evaluate the effects of pile cap upstream extension, pile group arrangement, and pile group upstream extension on the maximum scour depth. Each experiment was lasted to reach the equilibrium condition. It was conducted four long duration tests were performed to observe the effect of pile cap elevation on the temporal development of scour depth. In addition, effect of pile cap thickness on the maximum scour depth was tested. Each experiment was carried out under a steady-state clear water conditions. Moreover, 393 data points were collected from published papers. To fit a mathematical model on laboratory data ANN (FFBP) was used. The study includes the collected laboratory data to train and validate the networks. It also includes the utilization of past empirical methods of scour problem to obtain the dominant parameters of the problem. Based upon pile cap elevation, three combinations of dimensional data were used for the analysis of networks. A single layer FFBP with 10, 14, and 8 neurons was considered as a best model for three input combinations, respectively. A comparison between the produced results of ANN and existing empirical methods shows the capability of artificial neural network in predicting scour depth around complex pier. Developed mathematical model prediction was more precise than those given by existing methods because of low errors and high correlation coefficients. It shows that the neural networks predict scour depth more accurately than the existing method. Based upon the low errors, RMSE, and high correlation coefficients, R^2, the better procedure to estimate the scour depth could be selected. The results show that when the pile cap was above the initial bed level, case I, FFBP has a correlation coefficient, 0.71, and error, 0.66, that is better to compare to the empirical methods. Once pile cap was semi buried, case II, FFBP has a correlation coefficient, 0.67, and error, 0.70, that is better to compare to the empirical methods. The results show that the FFBP method has a good agreement with measured data. In case III, when the pile cap was completely buried, FFBP has a correlation coefficient, 0.89, and error, 0.58, that is better to compare to the empirical methods. It should be noted that the mathematical model has a fine accord with measured data to predict scour depth around complex bridge piers. Sensitivity analysis indicated that pile spacing width, longitudinal extension of pile group from column and column length are the most effective parameters on scour depth in each combination respectively.

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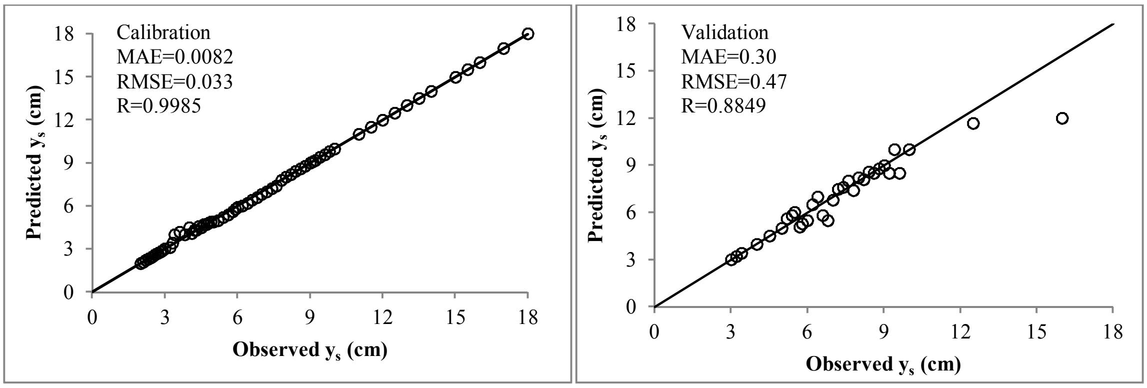


Fig. 1. Plot of observed and predicted scour depth for case I: (a) calibration and (b) validation

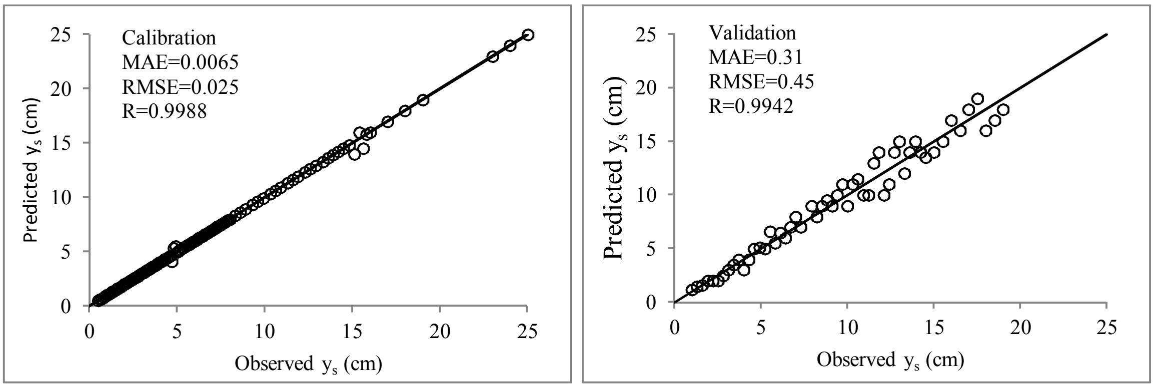


Fig. 2. Plot of observed and predicted scour depth for case II:: (a) calibration and (b) validation

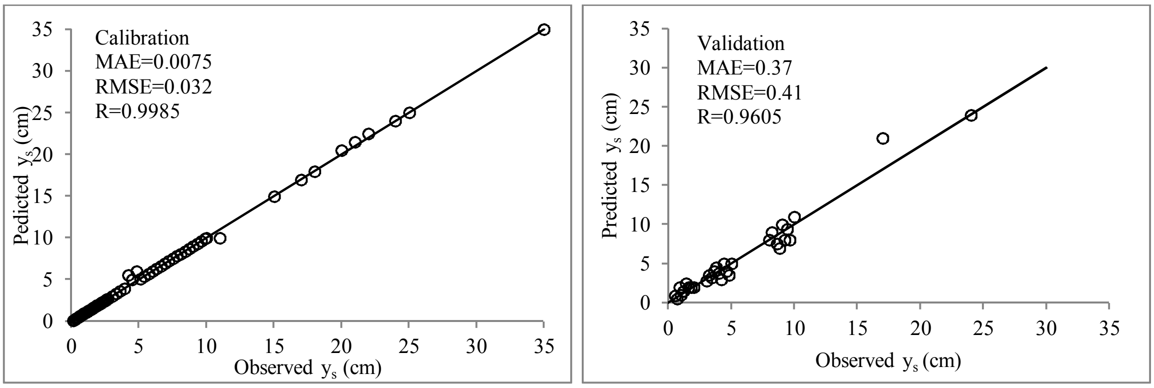
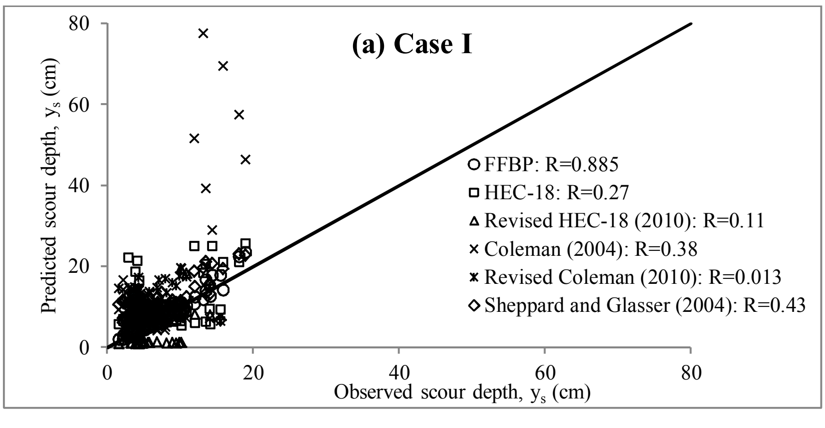
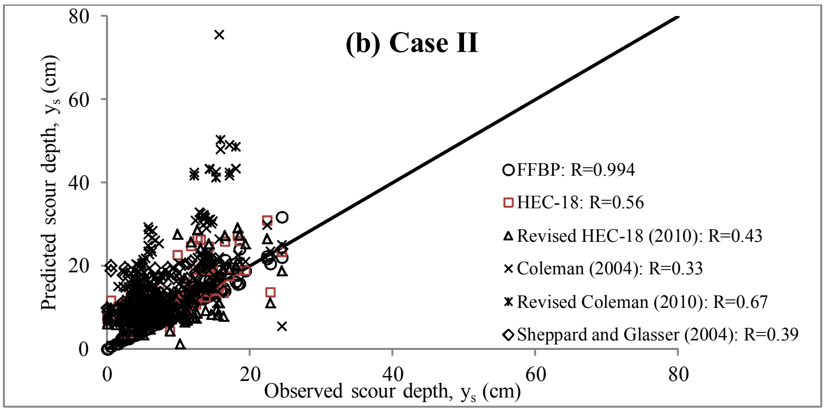


Fig. 3. Plot of observed and predicted scour depth using FFBP-model for case II (once pile cap was semi-buried): (a) calibration and (b) validation





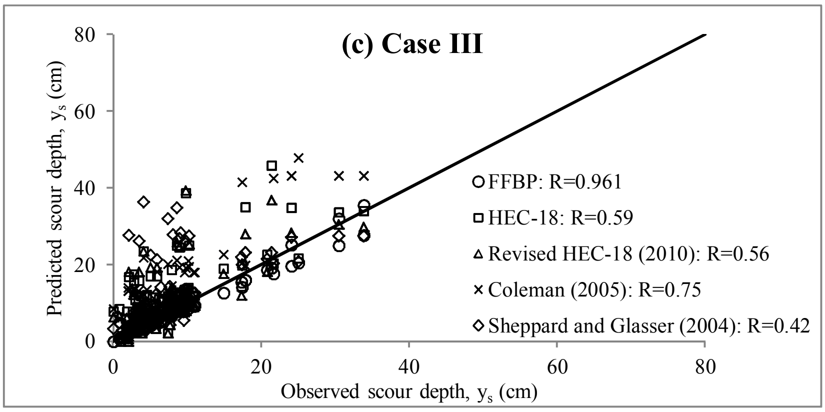


Fig. 4. Comparison of obtained results of scour prediction between FFBP and empirical methods for data sets: (a) case I, (b) case II, and (c) case III, respectively.