ADVANCES in NATURAL and APPLIED SCIENCES

ISSN: 1995-0772
EISSN: 1998-1090
2016 July 10(11): pages 71-78

Published BY **AENSI Publication**
http://www.aensiweb.com/ANAS
Open Access Journal

Modeling of Local Scour Depth Around Bridge Piers Using Artificial Neural Network

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Received 15 May 2016; Accepted 7 July 2016; Available 22 July 2016

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ABSTRACT

Bridges are one of the most important structures that must be protected from failure by safe design and continuous monitoring. In the present study artificial neural network (ANN) model with feed-forward back-propagation algorithm is developed to investigate the local scour depth around circular bridge piers using laboratory data of several researchers in addition to the laboratory data of this study under clear water conditions. Pier diameter (D), flow velocity (V), flow depth (y) and mean particle size (d_{50}) were selected to be input to the neural network. The results show that the artificial neural network is a good tool to predict the maximum local scour depth at bridge piers. Comparison the results with twelve predictive formulas showed an improved performance by using the artificial neural network model. Also it was found that pier diameter has the major effect on the scouring process, followed by flow velocity.

KEYWORDS: Artificial neural network, back-propagation, bridge pier, local scour.

INTRODUCTION

Bridges are one of the principle components of the transportation systems and their failure will result in economic losses as well as human life threat, therefore, there is need to protect them by continuing maintenance through proposing the required repair procedures. Bridges might fail due to three main reasons: collision, excessive loading and scour. Bridge scour has been reported all over the world as the most common factor for bridges failure, particularly in countries that are subject to floods induced by annual typhoons.

Arneson *et al*. [1] suggested that, the total scour at bridges can be divided into long-term degradation of the river bed, contraction scour at the bridge and local scour at the piers or abutments. Local scour can be defined as the removal of materials from around piers, abutments, spurs, and embankments. It is caused by an acceleration of flow and resulting vortices induced by obstructions to the flow.

The presence of the bridge piers in the river will alter flow patterns in the vicinity of the piers results in an increase in the sediments movement causing the phenomenon of scour. To avoid a failure of the bridges, the foundations depth (piers and abutments) should be deeper than the maximum scour depth in its life time, and the old bridges should be checked from time to time to evaluate the maximum scour depth around the bridge foundation to avoid bridge collapse.

Over the past decades many researchers studying the local scour (d_s) at bridge piers and variety predictive formulas was developed based on laboratory and field observations, such as Laursen and Toch [2], Jain and Fischer [3], Melville [4], Rui *et al*. and many other researchers, as shown in Table (1).

In the recent years, the application of Artificial Neural Networks (ANNs) is proposed to predict the local scour depth as an alternative to the predictive formulas, Kambekar and Deo [14] used ANNs to predict the scour

To Cite This Article: Saleh I. Khassaf and Ali Q. Abdulwhab., Modeling of Local Scour Depth Around Bridge Piers Using Artificial Neural Network. **Advances in Natural and Applied Sciences**. 10(11); Pages: 71-78

depth as well as scour width for group of piles. Lee *et al*. [15] developed ANN model with five inputs in normalized form to predict the local scour depth around bridge pier, the measured data of thirteen states in USA used to test the performance of the ANN model. Bateni *et al*. [16] showed that, ANN model with multi-layer perceptron using back-propagation algorithm (MLP/BP) provides a better prediction of scour depth than radial basis using orthogonal least-squares algorithm (RBF/OLS) and adaptive neuro-fuzzy inference system (ANFIS). Kaya [17] investigated different input variables with various ANNs models, the sensitivity analysis indicated that pier scour depth can be estimated using four variables: pier shape, pier skew, flow depth and flow velocity.

Table 1: Scour Depth Formulas Proposed from Previous Studies.

Author	Formula
Laursen and Toch (1956)	$d_s = 1.35\, a^{0.7} y^{0.3}$
Shen *et al*. (1969)	$d_s = 0.00022\, \mathrm{Re}^{0.619}$, $\mathrm{Re} = \frac{\rho V D}{\mu}$
Hancu (1971)	$\frac{d_s}{a} = 2.42\, (\frac{2V}{V_c} - 1)\, (\frac{V^2}{g\, a})^{1/3}$
Neil (1973)	$d_s = K_s\, a$
Bresusers *et al*. (1977)	$\frac{d_s}{a} = (\frac{2V}{V_c} - 1)\, (2 \tanh \frac{y}{a})$
Jain and Fischer (1979)	$\frac{d_s}{a} = 1.84\, \mathrm{Fr}_c^{0.25} (\frac{y}{a})^{0.3}$, $\mathrm{Fr}_c = \frac{V_c}{\sqrt{g\, y}}$
CSU (Richardson and Davis 1995)	$\frac{d_s}{y} = 2\, K_1 K_2 K_3 K_4 (\frac{a}{y})^{0.65} \mathrm{Fr}^{0.43}$, $\mathrm{Fr} = \frac{V}{\sqrt{g\, y}}$
Melville (1997)	$d_s = K_{yb} K_I K_d K_s K_\theta K_G$
Maatooq (1999)	$\frac{d_s}{a} = 0.519 + 2.5\, (\frac{V}{V_c} - 0.57)\, \frac{y}{a}$
Sheppard and Miller (2006)	$\frac{d_s}{a} = 2.5\, f_1 f_2\, (1 - 1.75\, (\ln \frac{V}{V_c})^2)$ $f_1 = \tanh (\frac{y}{a})^{0.4}$, $f_2 = \frac{a/d_{50}}{0.4\, (a/d_{50})^{1.2} + 10.6\, (a/d_{50})^{-0.13}}$
Khwairakpam *et al*. (2012)	$\frac{d_s}{a} = (0.744\, (\frac{y}{a}) - 0.367)\, \mathrm{F}_{d50} + (-2.348 (\frac{y}{a}) + 2.683)$ $\mathrm{F}_{d50} = \frac{V}{\sqrt{\Delta g\, d_{50}}}$, $\Delta g = \frac{\rho}{\rho_s} - 1$
Rui *et al*. (2013)	$\frac{d_s}{a} = K_h K_d K_I$

Where, a = Pier width, D = Pier diameter, d_s = Maximum local scour depth, d_{50} = Mean sediment size,Fr = Froude number, $\mathrm{Fr_c}$ = Critical Froude number, $\mathrm{F_{d50}}$ = Densimetric Froude number, g = Gravitational acceleration, K_1 = Correction factor for pier nose shape, K_2 = Correction factor for the angle of attack of the flow, K_3 = Correction factor for bed conditions, K_4=Correction factor for armoring by bed material size, K_d = Sediment size factor, K_G = Factor of channel geometry effect, K_h = Shallowness factor, K_I = Flow intensity factor, K_s = Pier shape factor, K_{yb} = Flow depth-pier size factor, K_θ = Pier alignment factor, Re = Reynolds number for the pier , V = Flow velocity, V_c = Critical flow velocity, y = Flow depth,Δg = Reduced gravitational acceleration, ρ = Water density, ρ_s = Sand density, μ = Dynamic viscosity of the water.

In this research, feed-forward neural network with back-propagation algorithm will be used to predict the maximum local scour depth around single cylindrical bridge pier under clear water conditions and comparison of the results with twelve of the most common predictive formulas, listed in Table (1).

Experimental Work:

Experimental measurements were conducted at the university of Basrah, college of engineering, to analyze and observe the local scour around bridge piers experimentally. All laboratory experiments were conducted under clear water conditions. Flume with a total length of 5.72 m, width 0.615 m and 0.2 m height was used in the experiments. At the entrance of the flume there is a mesh screen to establish steady flow conditions. Discharge was measured by sharp crested rectangular weir. Depth of flow was controlled by an adjustable tail gate at end of the flume and measured by point gauge (± 0.1 mm accuracy).

Uniform sand with d_{50} = 0.348 mm used as a bed sediments. Single vertical cylindrical piers were made of wood used in the experiments, place in the middle sand area. before each experiment, the sand bed is perfectly leveled, Then the flume is filled with water gradually and the pump starts with low velocities until the desired value is reached. At the end of each run the flume is drainage and the scour depth is measured with a point gauge. The experimental data is presented in Table (2).

Table 2: Experimental Data.

Run No.	d_{50} mm	D mm	V m/s	y mm	d_s mm
1	0.348	19	0.172	45	26.3
2	0.348	24.4	0.172	45	36.6
3	0.348	35.2	0.172	45	42.2
4	0.348	40.5	0.172	45	47
5	0.348	49	0.172	45	53.4
6	0.348	24.4	0.141	40	24

7	0.348	24.4	0.16	40	30
8	0.348	24.4	0.18	40	34.8
9	0.348	24.4	0.2	40	42
10	0.348	24.4	0.2162	40	46
11	0.348	49	0.1768	35	47.5
12	0.348	49	0.1768	40	51
13	0.348	49	0.1768	44	53
14	0.348	49	0.1768	48	57
15	0.348	49	0.1768	51	61

Artificial Neural Network:

Artificial neural network is type of artificial intelligence (computer system) that attempt to simulate and mimic the way of the human brain in processing and storage information. ANN composed of collection of interconnected processing elements called neurons or nodes, it works by creating connections between the nodes and the strength of these connections called weights. neurons grouped in layers and most of ANN models consist of three or more layers (input layer, hidden layers, output layer) as shown in Figure 1, The ANN system learns by determine the appropriate number of neurons in the hidden layer or hidden layers and adjusting the weights of the connections based upon the training data. Trial and error are the best way to determine the appropriate number of hidden neurons and the number of the hidden layers [18].

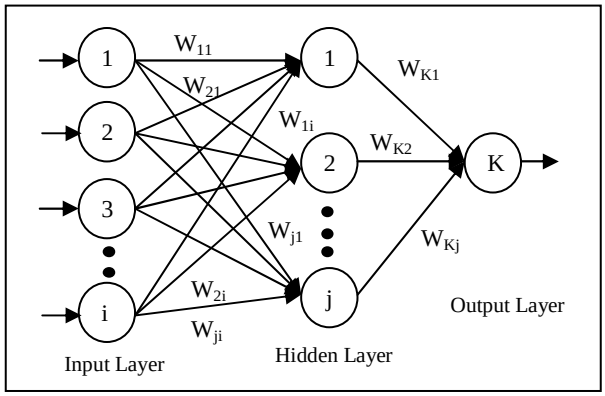

Fig. 1: Schematic diagram for ANN model.

Where, W_{ji} is the weight of the connection between the ith input layer neuron and jth hidden layer neuron, W_{Kj} is the weight of the connection between the jth hidden layer neuron and the kth output layer neuron.

The input data is first fed directly to the network through the input layer, and subsequently to the hidden layer to produce an expected result through the output layer. each node multiplies every input by corresponding weight and sums them together in addition to the bias to form the net input to the neuron, and then passes the net input through the transfer function to produce the node output. The transfer function for the hidden nodes is usually a sigmoid transfer function.

The ANN are trained with a set of input and known output data, and the procedure to know the performance of the network is based on the mean square error (mse) and the regression value (R), they can be calculated as below [19,20]:

$$\text{mse} = \frac{1}{n}\sum_{k=1}^{n}(T_k - O_k)^2 \quad (1)$$

$$R = \frac{\sum_{k=1}^{n}(T_k - \bar{T})(O_k - \bar{O})}{(n-1)S_T S_O} \quad (2)$$

$$S_T = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(T_k - \bar{T})} \quad (3)$$

$$S_O = \sqrt{\frac{1}{n-1}\sum_{k=1}^{n}(O_k - \bar{O})} \quad (4)$$

$$\bar{T} = \frac{1}{n}\sum_{k=1}^{n} T_k \quad (5)$$

$$\bar{O} = \frac{1}{n}\sum_{k=1}^{n} O_k \quad (6)$$

Where, T_k is the actual target, O_k is the network output, n is the number of data, $\bar{T}$ is the mean value of the targets, $\bar{O}$ is the mean value of the network output.

One is the best condition for the regression value and Zero is the best condition for the mean square error. After training the network and get best training performance it should test the network with new data never been

presented in the training data and in the range of the training data. Sometimes neural network give a perfect performance for the training data but it fails to produce a good results when applied to a new examples (over fitting), [21]. Therefore, it is necessary to test the network and check if it memorizing the relation between the inputs and outputs when applying to a new data in the future. And the network with best testing performance will be choose as the proposed network.

RESULTS AND DISCUSSIONS

A. Experimental Results:

The laboratory experiments addressed three cases, the effect of pier size, flow velocity and flow depth on the local scour, as show in Figures (2, 3 and 4) respectively. It is found that the larger pier diameter gives deeper local scour upstream of the pier. This is because the strength of the horseshoe vortex which is proportional to the diameter of the pier. Flow velocity increment leads to increase the flow intensity under the same conditions of flow depth and pier diameter, in turn, this will lead to more scour depth as velocity is increased under clear water conditions. Flow depth has a proportional effect on the local scour depth. The results have shown that the local scour depth increases as the depth of flow increases under the range of the flow depth during the experiments. this conforms with the previous researches in that: the scour depth is proportional to flow depth up to limiting value where this effect is vanished.

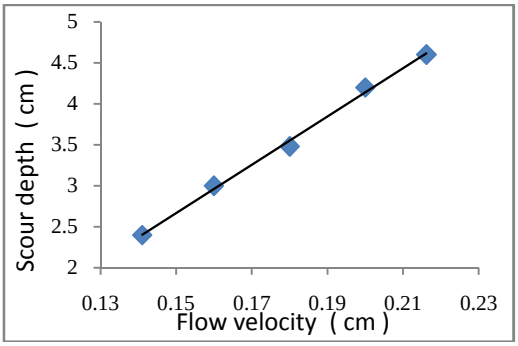

Fig. 2: Effect of pier diameter on the scour depth

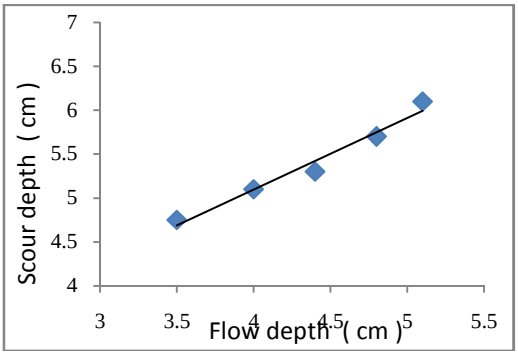

Fig. 3: Effect of flow velocity on the scour depth

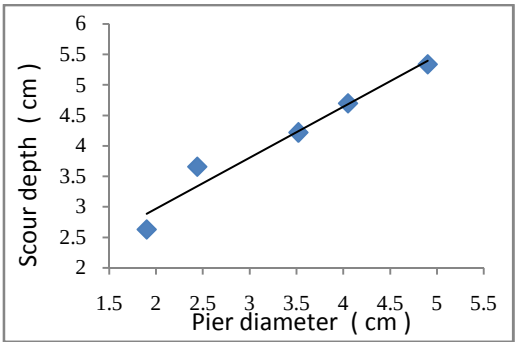

Fig. 4: Effect of flow depth on the scour depth

B. Artificial Neural Network Results:

Feed-forward neural network with back-propagation algorithm was used in this research to predict the maximum local scour depth around bridge pier. Trial and error process was used to configure the neural networks parameter such as the training functions, number of the hidden layers and the number of the neurons in the hidden layers. Logsig transfer function was used in the hidden layer(s) and Purelin transfer function in the output layer. The network was trained with laboratory data from previous researchers shown in Table 3. The laboratory data of Yanmaz and Altinbilek [22] was used to test the network performance. Table 4, shows the input and output variables for the training and testing and the range of each one of them.

Table 3: Training Data

The Researcher	Number of Data set
Chabert and Engeldinger	12
Dey *et al*. [24]	18
Maatooq J.S.	82
Mia and Nago	5

Table 4: Training and Testing Variables and the Range of them

Item	Variables	Range of Data	
		Training	Testing
Input variables	d_{50} (cm)	0.026 – 0.3	0.084 – 0.107
	D (m)	0.01 – 0.15	0.047 – 0.067
	V (m/s)	0.128 – 0.522	0.166 – 0.362
	y (m)	0.02 – 0.35	0.045 – 0.165
Output variables	d_s (m)	0.0113 – 0.175	0.032 – 0.107

ANN was trained and tested with one and two hidden layers with different number of nodes (1–20) in each hidden layer, as shown in Table (5). Several training functions was examined to reach the best approximations.

Table 5: ANN Performance with One Hidden Layer and Two Hidden Layers

Training function	One Hidden Layer				Two Hidden Layers			
	Nodes No.	mse (test) $\times 10^{-4}$	R (test)	Epoch	Nodes No.	mse (test) $\times 10^{-4}$	R (test)	Epoch
trainlm	19	0.29363	0.95924	17	12-3	0.26916	0.96873	46
trainrp	9	0.37733	0.94761	100	2-5	0.39655	0.94623	473
traingda	19	0.52304	0.94109	669	5-9	0.74826	0.92518	193
traingdx	19	0.45525	0.93719	316	8-20	0.49918	0.94346	2121
traincgf	3	0.39637	0.94624	79	7-20	0.59609	0.91539	48
traincgp	19	0.55217	0.92923	8	18-18	1.5486	0.76494	17
traincgb	16	0.41094	0.95476	137	7-20	0.58251	0.91807	32
trainscg	3	0.41031	0.94644	184	3-14	0.36133	0.95046	198
trainbfg	2	0.37213	0.94882	163	11-19	0.61022	0.9132	30
trainoss	16	0.36099	0.95173	1600	3-6	0.37339	0.95157	12000
traingda	4	6.3467	0.81467	100000	9-17	4.5898	0.73305	30000
traingdm	4	6.3467	0.81465	100000	9-17	4.5875	0.73322	30000

As can be seen in Table 5, (trainlm) training function gave the best testing performance with one and two hidden layers. There is no big difference between the results but using two hidden layers gave the best performance with mse = 0.26916×10^{-4} and R = 0.96873, therefore, it can be chosen as the proposed network to predict the local scour depth. Figures 5 and 6, show the regression and mse of the proposed network respectively. Table 6, shows the specifications of the proposed network.

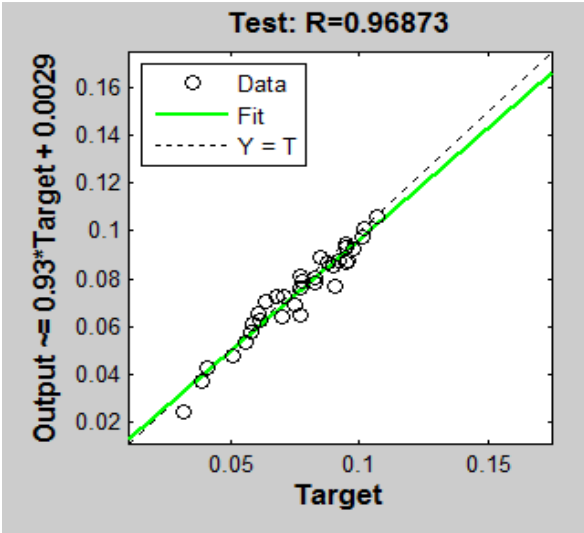

Fig. 5: Regression of the Proposed Network

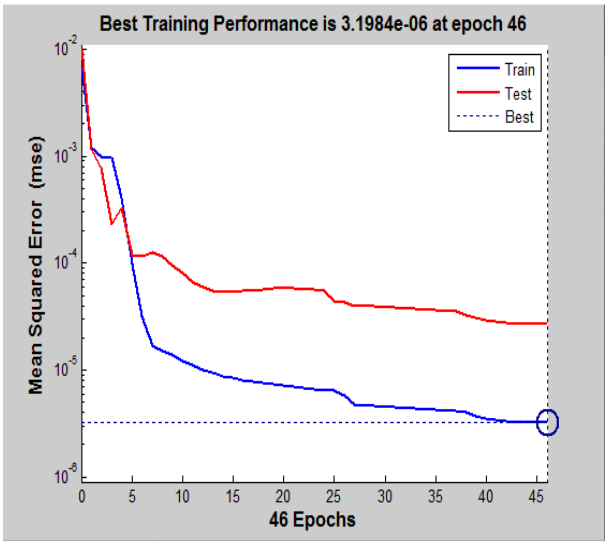

Fig. 6: Performance of the proposed network

Table 6: Specifications of the Proposed Network

Item	Description	
No. of nodes in the input layer	4	
No. of hidden layers	2	
No. of nodes in the hidden layers	First layer	12
	Second layer	3
Type of activation function	First hidden layer	logsig
	Second hidden layer	logsig
	Output layer	purelin
Training function	Levenberg-marquardt (trainlm)	
No. Nodes in the output layer	1	

C. Importance of the Input Variables:

Artificial neural network can be used to find the significant input variables that have the most effect on the scouring process and the prediction of the neural network. Test runs were conducted without containing a particular one input variable among the four inputs. The results are shown in Table (7). It is showed that the pier diameter has the most effect on the local scour, followed by the flow velocity.

Table 7: Input variables importance

Case	mse× 10^{-4} (Test)	R (Test)
All inputs	0.26916	0.96873
No d_{50}	1.0032	0.86557
No D	3.1935	0.77783
No V	2.4934	0.68938
No y	0.66757	0.94003

D. Comparison with Previous Formulas:

Experimental data of this study in addition to the test data of yanmaz and altinbilek [22] were applied to the proposed neural network and the previous formulas in Table 1, to show their performance. Figure (7) shows the performance of ANN and the predictive formulas.

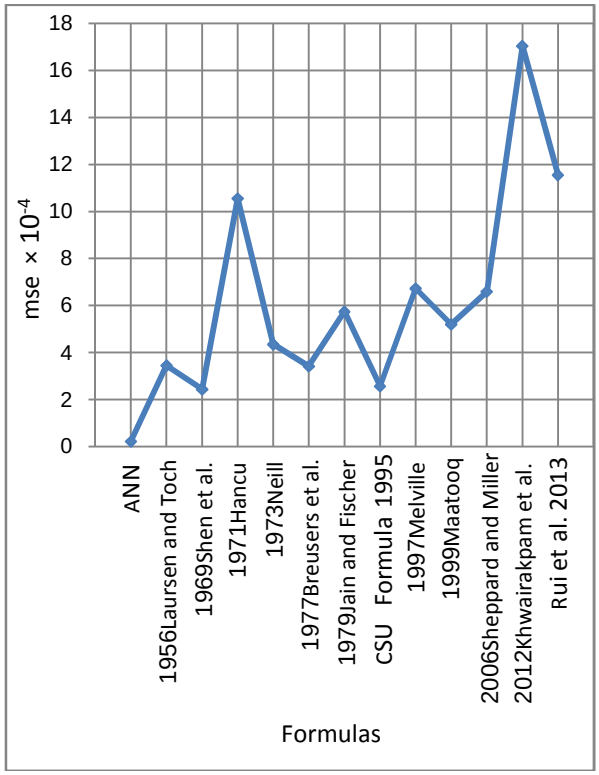

Fig. 7: mse of the ANN and the predictive formulas

From Figure 7, it is found that the ANN model gave the best approximation to the actual values from the previous formulas with mse = 0.216239× 10^{-4}. Also, it can be seen that, shen *et al*. [6] and CSU [10] formulas gave a good approximation among the twelve formulas.

Conclusions:

In this paper, the application of Artificial Neural Network is used to predict the maximum local scour depth at cylindrical bridge piers. it is found that Feed-forward neural network with back-propagation algorithm has proved to be a good tool for predicting the local scour depth at bridge piers and much more accurate than the predictive formulas used in this study. By making the sensitivity analysis to the input variables, it is found that pier diameter has the significant effect on the local scour depth prediction followed by flow velocity. Form Figure 7, it can be found that Shen *et al*. [6] and CSU [10] formulas are the best among the twelve formulas. The laboratory experiments show that both pier diameter and flow velocity are directly proportional with the local scour depth. Also, it is shown that the local scour depth is increased as the flow depth increased under the limitation of the experiments.

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