Artificial Neural Network to Predict Equilibrium Local Scour Depth around Semicircular Bridge Abutments

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Abstract
Local scour around bridge abutment is a common problem encountered worldwide. Much experimentation has been carried out in this field and the equations derived so far are applicable to particular circumstances only. In this paper, Artificial Neural Network (ANN) approach has been applied to the problem of scour around semicircular bridge abutments. Multilayer Perceptron (MLP) with single hidden layer and Radial Basis Function (RBF) network have been trained with the experimental data from literature and an appropriate model of each of the network is identified. The performance of the developed models has been evaluated using Root Mean Square Error (RMSE) and Correlation Coefficient (CC). A sensitivity analysis of input parameter has been carried out. The accuracy of the trained model has been evaluated against some of the empirical models available in the literature. Experimental results show the suitability and reliability of application of ANN for scour depth prediction around bridge abutments.

Key words – ANN, MLP, RBF, Scour

1. Introduction

Scour is the process of removing underwater sediment from the base of a structure by waves and currents (Jeng *et al.*, 2005). Due to the scouring action of the flow, bridge failures occur; and a large amount of money is spent every year to repair or replace those bridges. The number of abutment is much more than the number of piers, as most of bridges is of single span and hence, most of the repairing amount is spent due to abutment scour (Richardson *et al.*, 1993). Thus, scour around bridge abutment is a severe hazard to the performance of bridges. It is essential to understand the scouring process in the design of foundations of bridge structure. Scour-depth is an important parameter for determining the minimum depth of foundations. Extensive experimental investigation has been conducted to determine a method of predicting scour depth for various abutment situations. The empirical formulae developed so far are suitable to a particular abutment condition and the results of each formula highly differ with other (Bateni *et al.*, 2007). Artificial Neural Networks (ANNs) is an alternative method to overcome the variation of physical modeling and is a good function approximator. Neural networks can map a random input pattern to a random output pattern (Hassoun, 2002). Neural networks have been used effectively in a number of applications including prediction, diagnostics and classification. Different researchers (Liriano and Day, 2001; Nagy *et al.*, 2002; Kambekar and Deo, 2003; Agarwal *et al.*, 2005; Lee *et al.*, 2007;

Soliman, 2007; Azamathulla *et al.*, 2008; Begum *et al.*, 2011) have applied the ANN to analyse various civil and hydraulic engineering problems. In this paper, ANN models have been developed to estimate the scour depth around semicircular abutments using scour data from the literature.

The remaining of this paper is organized as follows: Section 2 includes a brief introduction about equilibrium local scour depth around semicircular abutment. The ANN models developed for scour depth prediction around semicircular abutment are introduced in section 3. Section 4 presents the experimental results and section 5 concludes the paper.

2. Maximum Equilibrium Local Scour Depth around Semicircular Abutment

Maximum equilibrium local scour depth at a semicircular abutment in uniform non-cohesive bed sediments depends on the variables characterizing the fluid properties, flow conditions, bed sediment properties and size of the abutment. The following functional relationship describes the maximum equilibrium local scour depth (Dey and Barbhuiya, 2005):

$$d_{se} = f_1(U, \rho, \rho_s, g, l, \nu, h, d_{50}) \tag{1}$$

where, U = average velocity of approach flow, ρ = mass density of the fluid, ρ_s = mass density of the sediment, g = acceleration due to gravity, l = length of abutment, ν = kinematic viscosity, h = approaching flow depth, d_{50} = median grain size and d_{se} = equilibrium scour depth.

Since, ρ, ρ_s, g and ν are constant for given sediment and fluid, the relationship between d_{se} and its dependent variables can be expressed as:

$$d_{se} = f_5(l, d_{50}, h, U) \tag{2}$$

3. Artificial Neural Network Model

In this study, Multilayer Perceptron (MLP) with single hidden layer and Radial Basis Function (RBF) network are implemented. The networks have been trained with the experimental scour data from the literature and an appropriate model of each of the network is identified. This section presents a brief introduction to MLP and RBF network models.

3.1. *Multilayer Perceptron Network*

The MLP network with single hidden layer used in the present study is shown in Fig. 1. The network has been trained with backpropagation learning algorithm with input parameter from Eq. 2. This algorithm adjusts the weights of the network so that the quadratic error between the desired and actual output is minimum (Hassoun, 2002; Fujail *et al.*, 2011). MLP is a universal function approximator and hence it is suitable for prediction.

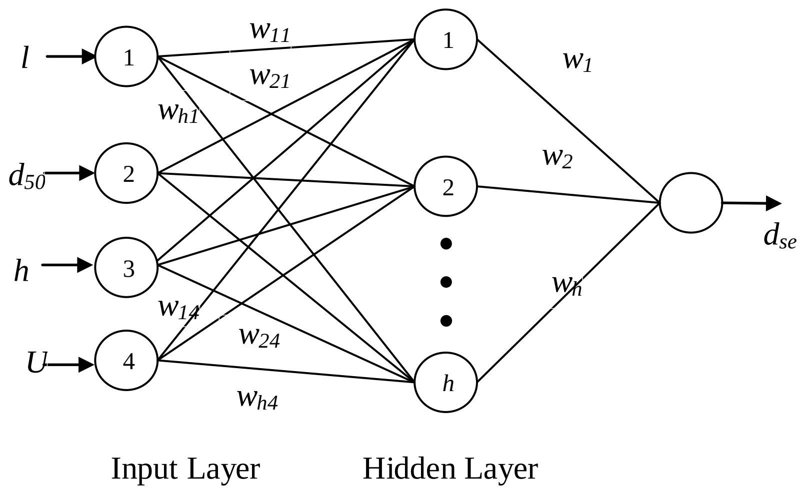

Fig.1 MLP Network

Output Layer

The output (z_j) of the j^{th} hidden node is given by

$$z_j = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{3}$$

where, x_i is the input, n is the number of input nodes, w_{ji} is the weight between j^{th} hidden node and i^{th} input node and f is the transfer function associated with j^{th} hidden node.

The output of the network is derived from

$$d_{se} = f\left(\sum_{j=1}^{h} w_j z_j\right) \tag{4}$$

where, h is the number of hidden nodes.

The ANN model implemented in this study includes log-sigmoid transfer function in the hidden layer as well as in the output layer, which can be expressed as

$$\log sig(x) = \frac{1}{(1+\exp^{(-x)})} \tag{5}$$

3.2. *Radial Basis Function Network*

The RBF network with an input layer, a hidden layer and an output layer used in the present study is shown in Fig. 2. The input layer is made up of source nodes. The hidden layer has sufficient dimensions, which applies a non-linear transformation of the input domain to a higher dimensional domain such that the training patterns can be linearly separated. The output layer provides the response of the network to the input patterns applied to the source nodes (Kim *et al.*, 2005). Various studies for RBFs have been conducted to determine centres and widths. Kil (1993) proposed the supervised selection of kernel centres algorithm. At each step, the data point that generates large error is added as a new centre. This approach has been used in this study.

In the present study, Gaussian transfer functions are used in the hidden layer neurons whose outputs are inversely proportional to the distance from the center of the neuron.

The output of the j^{th} hidden node is derived from the following expression:

$$\phi_j(x) = \exp\left(-\frac{\left\|x-\mu_j\right\|^2}{2\sigma_j^2}\right) \tag{6}$$

where, σ_j and μ_j are the width and centre of the j^{th} hidden unit, respectively and the norm is the Euclidean norm. The transfer function of the output node is linear. Thus, the output of the network is given by the following expression

$$d_{se}(x) = \sum_{j=1}^{h} w_j \phi_j(x) \tag{7}$$

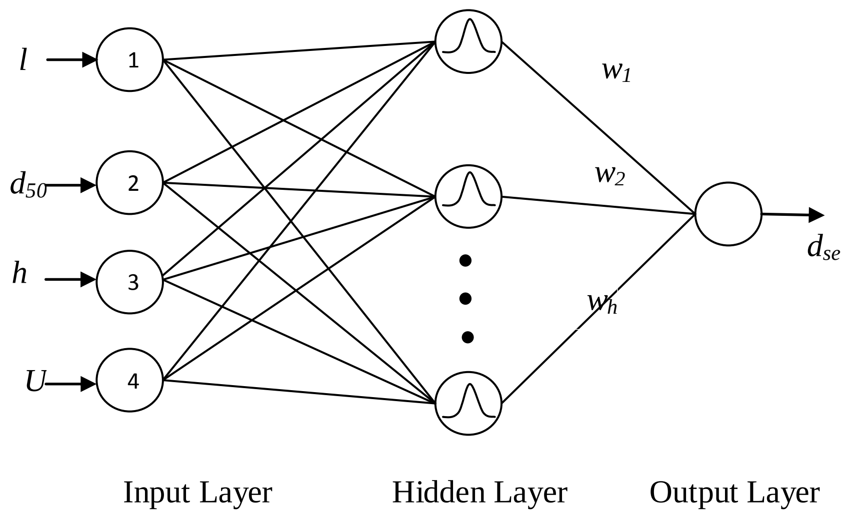

Fig. 2 RBF Network

3.3. *Training of Neural Network*

The input-output parameter used to train the network is expressed in Eq. 2. There are four input pattern (l, d_{50}, h, and U) and the equilibrium scour depth (d_{se}) is the output pattern. The experimental data reported by Dey and Barbhuiya (2005) is used in this study. The experimentation was conducted in a 20 m long, 0.9 m wide and 0.7 m deep horizontal flume with uniform non-cohesive bed-sediment. The data set consisting of five sets of data with a total of 99 data points which has been divided randomly into a training set and a testing set. The training set consists of 79 data points and testing set consists of 20 data points.

The data of input and output variable were first normalized within the range 0.1− 0.9 as follows:

$$x_N = \frac{0.9 - 0.1}{x_{\max} - x_{\min}}(x - x_{\min}) + 0.1 \tag{8}$$

where, x_N is the normalized value of x, x_{max} and x_{min} are the maximum and minimum value of each parameter in the original data. The normalization is done for effective training of the network.

The network has been trained with the normalized data, and the weights (w) were determined in such a way as to minimize the following cost function:

$$E = \frac{1}{2}\sum_{p=1}^{N}(t^p - y^p)^2 \tag{9}$$

where, t^p, y^p are target and network output for p^{th} training pattern and N is the total number of training patterns.

The optimum neural networks configurations are determined by trial and error method with an objective to minimize the difference among the network predicted values and the target values. The performance of each configuration was evaluated based on the root mean square error (RMSE) and correlation coefficient (CC) as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{p=1}^{N}\left(t^p - y^p\right)^2} \tag{10}$$

$$CC = \frac{\sum_{p=1}^{N}\left(y^p - \bar{y}\right)\left(t^p - \bar{t}\right)}{\sqrt{\sum_{p=1}^{N}\left(y^p - \bar{y}\right)^2 \sum_{p=1}^{N}\left(t^p - \bar{t}\right)^2}} \tag{11}$$

where, $\bar{y}$ and $\bar{t}$ are average over network and target outputs.

The optimal configuration, based upon minimizing the difference between the neural networks predicted outputs and the target outputs, corresponds to the minimum value of RMSE and the maximum value of CC.

4. Results and Discussion

The MLP and RBF neural network models are implemented in Matlab 7.3 environment. The training and testing results obtained are used to form an ANN model that can estimate local scour depth for a variety of abutments situations. The reliability of the predicted values not only depends on the ANN structure but also on the input data. To get the reliable results, the input data needs to be trustworthy. The input data used for training the ANN models in the present study has been collected from published literature and thus are assumed to be reliable.

The training dataset is used to train the network and testing dataset is used to check the generalization capability of the network. The next step is to select the optimum network architecture. In developing the optimum network architecture, the individual test cases were ranked according to the magnitude of RMSE and CC. The model having the minimum RMSE and maximum CC is selected as the optimum. The optimum MLP model among 260 tested cases is selected and plotted in Fig. 4 and the corresponding training results is plotted in Fig. 3. Similarly, the training and testing results of the optimum RBF model among 246 tested cases are plotted in Fig. 5 and Fig. 6 respectively. In the interest of brevity, a few cases of training and testing results obtained with MLP and RBF networks are tabulated in Table 1 and Table 2 respectively.

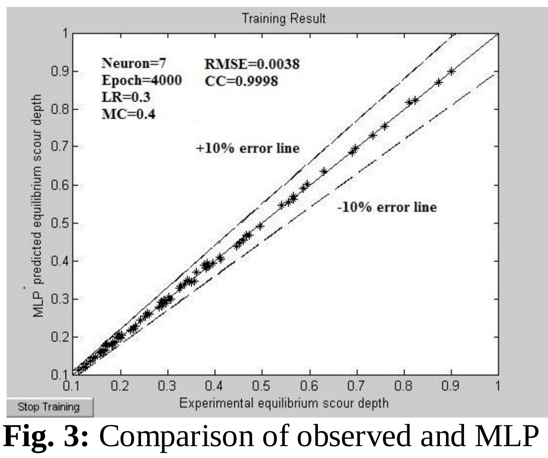

Fig. 3: Comparison of observed and MLP predicted equilibrium scour depth (Training)

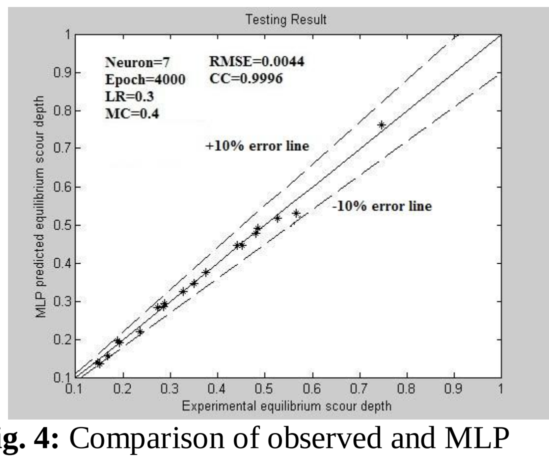

Fig. 4: Comparison of observed and MLP predicted equilibrium scour depth (Testing)

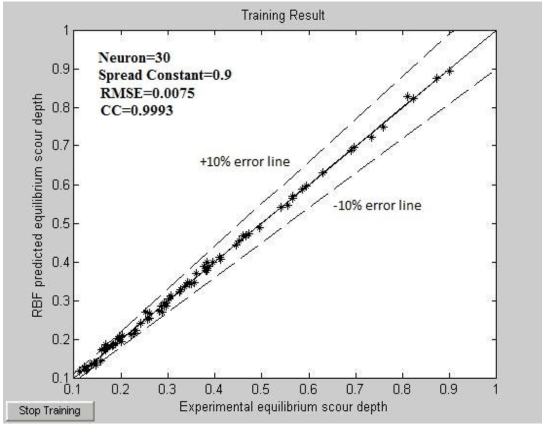

Fig. 5: Comparison of observed and RBF predicted equilibrium scour depth (Training)

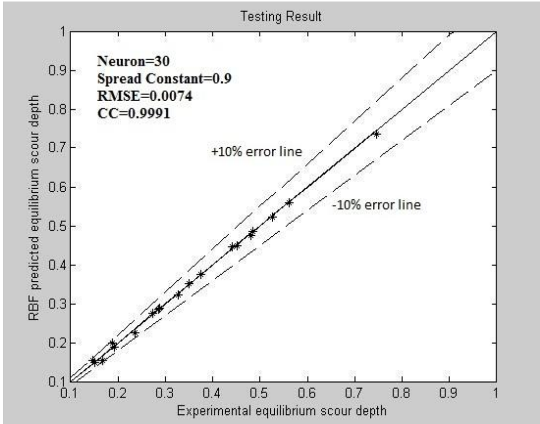

Fig. 6: Comparison of observed and RBF predicted equilibrium scour depth (Testing)

Network Parameters		Training		Testing	
Epoch	Neuron	RMSE	CC	RMSE	CC
3000	3	0.0190	0.9953	0.0218	0.9917
	4	0.0163	0.9966	0.0249	0.9891
	5	0.0074	0.9993	0.0255	0.9891
	6	0.0079	0.9992	0.0139	0.9976
	7	0.0041	0.9998	0.0436	0.9655
	8	0.0023	0.9999	0.0232	0.9906
4000	3	0.0218	0.9939	0.0194	0.9940
	4	0.0159	0.9968	0.0183	0.9943
	5	0.0074	0.9993	0.0101	0.9982
	6	0.0096	0.9988	0.0171	0.9952
	7	0.0038	0.9998	**0.0044**	**0.9996**
	8	0.0020	0.9999	0.0213	0.9921
5000	3	0.0234	0.9930	0.0207	0.9927
	4	0.0150	0.9971	0.0143	0.9973
	5	0.0081	0.9992	0.0144	0.9966
	6	0.0055	0.9996	0.0098	0.9985
	7	0.0037	0.9998	0.0173	0.9947
	8	0.0044	0.9997	0.0218	0.9921
6000	3	0.0213	0.9941	0.0246	0.9890
	4	0.0140	0.9974	0.0154	0.9956
	5	0.0068	0.9994	0.0092	0.9987
	6	0.0051	0.9997	0.0120	0.9975
	7	0.0046	0.9997	0.0203	0.9929
	8	0.0024	0.9999	0.0125	0.9974

Table 1. Training and Testing Results of MLP

Network Parameters		Training		Testing	
Neuron	Spread Constant	RMSE	CC	RMSE	CC
27	0.4	0.0180	0.9958	0.0319	0.9843
	0.5	0.0109	0.9985	0.0148	0.9969
	0.6	0.0091	0.9989	0.0128	0.9973
	0.7	0.0091	0.9989	0.0152	0.9962
	0.8	0.0098	0.9988	0.0151	0.9971
	0.9	0.0086	0.9991	0.0105	0.9980
	1.0	0.0095	0.9989	0.0121	0.9979
28	0.4	0.0177	0.9959	0.0311	0.9851
	0.5	0.0102	0.9987	0.0151	0.9968
	0.6	0.0089	0.9990	0.0131	0.9973
	0.7	0.0088	0.9990	0.0143	0.9965
	0.8	0.0094	0.9989	0.0127	0.9978
	0.9	0.0081	0.9992	0.0094	0.9985
	1.0	0.0091	0.9989	0.0128	0.9979
29	0.4	0.0171	0.9963	0.0286	0.9874
	0.5	0.0099	0.9987	0.0141	0.9972
	0.6	0.0083	0.9991	0.0119	0.9977
	0.7	0.0078	0.9992	0.0097	0.9985
	0.8	0.0090	0.9990	0.0133	0.9976
	0.9	0.0077	0.9992	0.0078	0.9989
	1.0	0.0089	0.9990	0.0128	0.9983
30	0.4	0.0152	0.9970	0.0277	0.9883
	0.5	0.0096	0.9988	0.0129	0.9977
	0.6	0.0078	0.9992	0.0096	0.9986
	0.7	0.0075	0.9993	0.0103	0.9982
	0.8	0.0090	0.9990	0.0136	0.9973
	0.9	0.0075	0.9993	**0.0074**	**0.9991**
	1.0	0.0087	0.9990	0.0116	0.9986

Table 2. Training and Testing Results of RBF

The selected cases of MLP and RBF models with optimum RMSE value 0.0044 and 0.0074, and CC value 0.9996 and 0.9991 obtained during testing respectively are highlighted in bold in the Tables 1-2. The MLP configuration having one hidden layer with 7 neurons, epochs equal to 4000, learning rate of 0.3 and a momentum constant of 0.4 was selected as the optimum model. Whereas, RBF model with 30 hidden layer neurons and spread constant of 0.9 was selected as optimum. The output of the ANN models have been compared with the results of three existing empirical equations proposed by Froehlich (1989), Kandasamy and Melville (1998) and Dey and Barbhuiya (2005) using the same dataset and the result is tabulated in Table 3. It can be concluded from Table 3 that ANN models provide improved prediction of scour depth than the existing formulae.

Method	RMSE	CC
ANN (MLP)	0.0038	0.9998
ANN (RBF)	0.0075	0.9993
Froehlich (1989)	0.1473	0.4953
Kandasamy and Melville (1998)	0.0795	0.5907
Dey and Barbhuiya (2005)	0.0130	0.9827

Table 3. Comparison of MLP and RBF Network with Existing Formulae

Finally, sensitivity analysis was carried out to determine the relative significance of each of the input parameters on the scour depth. Sensitivity analysis with the best neural network configuration shows the relative influence of various input parameters. This was performed with the best ANN configurations. To carry out the sensitivity analysis, one of the input parameter is removed in each case, and the results obtained from MLP and RBF network are tabulated in Table 4 and Table 5. From Tables 4-5, it can be concluded that for both MLP and RBF networks the abutment length (l) is most sensitive to scour depth than other parameters. Whereas, the height of the flow (h) is least sensitive to scour depth.

Method	RMSE	CC
MLP with l, d_{50}, h, and U	0.0044	0.9996
MLP without l	0.1196	0.8275
MLP without d_{50}	0.0275	0.9906
MLP without h	0.0049	0.9997
MLP without U	0.0063	0.9995

Table 4. Sensitivity Analysis Results for the Parameters in Eq.1

Method	RMSE	CC
RBF with l, d_{50}, h, and U	0.0075	0.9993
RBF without l	0.1207	0.6160
RBF without d_{50}	0.0118	0.9963
RBF without h	0.0068	0.9988
RBF without U	0.0206	0.9888

Table 5. Sensitivity Analysis Results for the Parameters in Eq.1

5. Conclusion

In this study, ANN *viz*. MLP and RBF networks have been used to predict the maximum local scour depth around bridge abutment. Both the models provide results with a very good level of accuracy with CC greater than 0.99, when the MLP and RBF predicted results are compared with the experimental results. From the Figs. 3-6, it is observed that the predicted values are within ±10% error from the observed values. From Table 3, it can also be concluded that MLP gives more accurate result than RBF network. From the sensitivity analysis with the best neural network configurations it is observed that abutment length (l) is most sensitive and height of the flow (h) is the least sensitive to maximum local scour depth.

The present study has been carried out with MLP network having single hidden layer and RBF network. Experimental results show the suitability of ANN for prediction of scour depth around bridge abutment. Further experimentation needs to be carried out with other neural network models as well as with other hybrid models *viz.* neuro-fuzzy and neuro-genetic models. Further research will be conducted towards the issues that may influence the performance of the developed models, *viz.* the network architecture, optimization of the connection weights and model validation.

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