Neuro-genetic Approach to Predict Scour Depth Around Vertical Bridge Abutment

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Abstract Scour is caused by the erosive action of flowing water. Although, different researchers have proposed various empirical models to predict the equilibrium local scour depth around bridge abutment, these are suitable to a particular abutment condition. In this study, an integrated model that combines genetic algorithms (GA) and multilayer perceptron (MLP) network, a class of artificial neural network (ANN), is developed to estimate the scour depth around vertical bridge abutment. The equilibrium scour depth was modeled as a function of four affecting parameters of scour, abutment length, median grain size, approaching flow depth, and average approach flow velocity, and these parameters are considered as input parameter to the MLP model. The efficiency of the developed models is compared with the empirical equations over a dataset collected from literature. The MLP is found to outperform the empirical equations for the dataset considered in the present study. The performance of the best case MLP is further improved by applying GA for weight initialization. The results indicate that the GA-based MLP is more effective in terms of accuracy of predicted results and is a promising approach compared to MLP as well as the previous empirical approaches in predicting the scour depth at bridge abutments.

Keywords Scour depth prediction · Artificial neural network · Genetic algorithm

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K.N. Das et al. (eds.), *Proceedings of Fourth International Conference on Soft Computing for Problem Solving*, Advances in Intelligent Systems and Computing 335,
DOI 10.1007/978-81-322-2217-0_13

1 Introduction

Scour is the process of removing underwater sediment from the base of a structure by waves and currents [1]. 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 numbers of piers, as most of bridges are of single span, and hence, most of the repairing amount is spent toward abutment scour [2]. According to the report published by the Department of Scientific and Industrial Research of New Zealand [3], 50 % of total expenditure was made to repair and maintain bridge damage, out of which 70 % was spent to repair abutment scour. Thus, estimation of the depth of local scour around bridge abutments is an important issue in the design of bridges.

The empirical formulae [4–7] developed through experimental investigation for predicting scour depth around abutment are suitable to particular abutment instances and the results of each formula significantly differ with each other. Artificial Neural Networks (ANNs) are alternative method to overcome the variation of physical modeling and is a good function approximator. ANNs have been widely applied in modeling complex problems in civil engineering. A review shows that the available literature on the application of ANN to the scour at abutments is limited. Kheireldin [8] applied the ANN to predict the maximum local scour depth around bridge abutments. Begum et al. [9] developed Multilayer perceptron (MLP) to predict scour around semicircular abutment. It is reported that MLP performs better than the empirical formulae as well as the radial basis function network. Begum et al. [10] also developed genetic programming model to predict the depth of scour around vertical abutment. It is observed from the available literatures that the soft computing models provide more accurate results than the empirical formulae.

The main objective of this paper was to investigate the performance of GA-based MLP (GA-MLP) relative to MLP and empirical formulae. In this paper, MLP and GA-MLP networks are applied to existing experimental data for local scour.

The remainder of this paper is organized as follows: A brief introduction about equilibrium scour depth is given in Sect. 2. Section 3 includes the empirical formulae for local scour at bridge abutments. Methodology is given in Sect. 4. The MLP and GA-MLP models developed for scour depth prediction around abutment are introduced in Sects. 5 and 6, respectively. Section 7 concludes the paper.

2 Equilibrium Local Scour Depth Around Bridge Abutment

Local scour is caused by the erosion of bed material from the base of abutment. It can be either clear-water or live-bed scour. Clear-water scour occurs where there is no movement of bed material into a scour hole during the time of scour. On the other hand, live-bed scour occurs when the scour hole is continuously fed with sediment by the approaching flow [11]. The dataset used in the present study involves clear-water condition.

Maximum equilibrium local scour depth around an abutment in a steady flow of uniform, cohesionless sediment depends on the fluid, flow, bed sediment, and abutment characteristics. Thus, the maximum equilibrium scour depth may be represented by the following functional relationship [12]:

$$d_{\mathrm{se}} = f_1(U, \rho, \rho_{\mathrm{s}}, g, l, v, h, d_{50}) \tag{1}$$

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

For a given fluid condition, ρ, ρ_{s}, g, and v are constant and thus the relationship between d_{se} and its dependent variables can be expressed as follows:

$$d_{\mathrm{se}} = f_2(l, d_{50}, h, U) \tag{2}$$

3 Empirical Formulae for Local Scour at Bridge Abutment

Four empirical formulae considered for evaluation in the present study are tabulated in Table 1.

In the above cases, abutment shape factor, K_{s}, is considered as 1 (one), which is the shape factor of vertical wall abutment.

Table 1 Empirical formulae for scour depth prediction around vertical bridge abutment

Author	Formula
Froehlich [4]	$\frac{d_{se}}{h} = 0.78 K_s K_\theta \left(\frac{l}{h}\right)^{0.63} F_r^{1.16} \left(\frac{h}{d}\right)^{0.43} \sigma_g^{-1.87} + 1$ where K_s = abutment shape factor, K_θ = abutment alignment factor, F_r = approaching flow Froude number, σ_g = geometric standard deviation, and d = median diameter of sediment particles
Kandasamy and Melville [5]	$d_{se} = K_s K\, h^n l^{1-n}$ where K_s is the shape factor, K and n are coefficients that are determined as follows: $K = 5$ and $n = 1$ for $h/l \leq 0.04$; $K = 1$ and $n = 0.5$ for $0.04 < h/l < 1$; and $K = 1$ and $n = 0$ for $h/l > 1$
Melville and Coleman [6]	$d_{se} = K_{hl} K_I K_{d_{50}} K_s K_\theta K_G$ where K_{hl} represents the effects of flow depth and abutment length, K_I is the flow intensity factor, $K_{d_{50}}$ is abutment length and sediment size effects factor, K_G represents the approach channel geometry factor, and K_s and K_θ are as defined in the previous equations
Dey and Barbhuiya [7]	$\frac{d_{se}}{l} = 7.281 F_e^{0.314} \left(\frac{h}{l}\right)^{0.128} \left(\frac{l}{d_{50}}\right)^{-0.167}$ where F_e = excess abutment Froude number.

4 Methodology

The ANN model development for scour depth prediction consists of 5 steps:

Step 1. The dataset for vertical wall abutment considered in the present study was collected from the literature [7, 12, 13]. It contains four independent parameters: length of the abutment, median grain size, depth of the flow, and average approaching flow and one dependent parameter, that is, depth of the scour. The dataset consists of 227 samples, out of which nine samples are removed as outlier.

Step 2. For effective training of the network, all data values were normalized within the range 0.1–0.9 with the following equation:

$$x_{\mathrm{N}} = \frac{0.9 - 0.1}{x_{\max} - x_{\min}}(x - x_{\min}) + 0.1 \tag{3}$$

where x is the data value, x_{N} is the normalized value of x, $x_{\max}$ is the maximum, and $x_{\min}$ is the minimum value in the original dataset. Next, the dataset was divided randomly into a training set and a testing set to train the network and assess the performance of the network, respectively. The training set consists of 80 % and the testing sets consists of 20 % data points.

Step 3. Network architectures and learning methods are selected. In the present study, MLP with single hidden layer is used which is shown in Fig. 1.

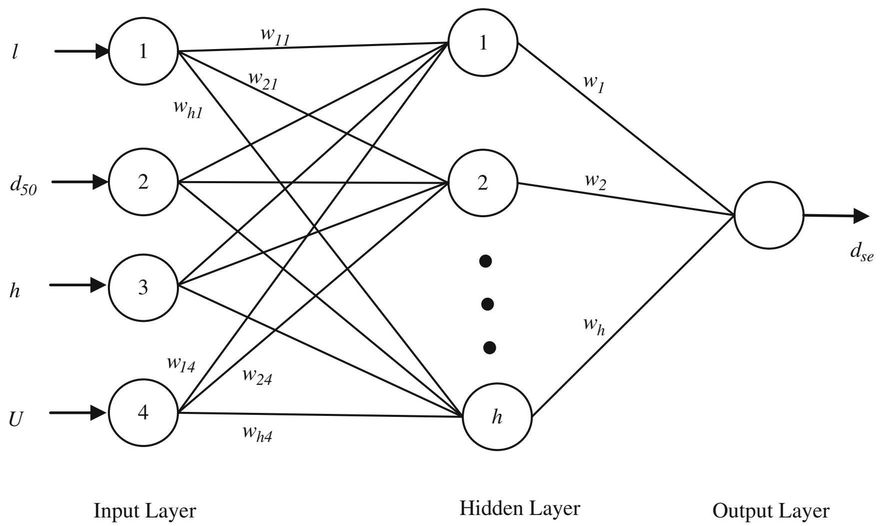

Fig. 1 MLP network

Step 4. Weights and other parameters, viz. learning rate (LR), momentum constant (MC), number of neuron in the hidden layer, and epochs are initialized. These parameters are modified with learning algorithms to get better performance of the network. Since there are four independent parameters that affect the extent of scour, the number of node in the input layer is four. There is only one output node that corresponds to the depth of scour. The networks have been trained several number of times to obtain the suitable number of nodes in the hidden layer, momentum values, learning rate, and number of iteration.

Step 5. Optimum network models are identified based on root mean square error (RMSE) and correlation coefficient (CC) between target and predicted values. The RMSE and CC are evaluated as follows:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(o_i - t_i)^2} \tag{4}$$

$$\mathrm{CC} = \frac{\sum_{i=1}^{n}(o_i - \bar{o})(t_i - \bar{t})}{\sqrt{\sum_{i=1}^{n}(o_i - \bar{o})^2 \sum_{i=1}^{n}(t_i - \bar{t})^2}} \tag{5}$$

where o_i and t_i are network and target output for the ith input pattern, $\bar{o}$ and $\bar{t}$ are the average of network and target outputs, and n is the total number of events considered.

To select the optimum architecture, each network is evaluated with testing dataset. The models with minimum RMSE and maximum CC during testing are selected as optimum.

5 Multilayer Perceptron

MLP is an important class of ANN. The schematic diagram of the implemented MLP models is shown in Fig. 1. The values of the independent parameters l, d_{50}, h, and U are fed in the network through the nodes in the input layer. The network is trained with Levenberg–Marquardt optimization algorithm and produces an expected result (d_{se}) in the output layer. The hidden layer of neurons enables the network to learn complex tasks by extracting meaningful features from the input patterns. The number of nodes in hidden layer is determined by trial and error method.

In Fig. 1, w_{11}, w_{21},…, w_{h4} are the weights between hidden and input layer and w_1, w_2, …, w_h are weight between hidden and output layer. The initial weights are generated by Nguyen–Widrow [14] method.

The network includes various activation functions in the hidden and output layer with different values of number of neurons, epochs, LR, and MC. The combinations

Table 2 MLP architectures

Activation function		No. of hidden neuron	Learning rate	Momentum	Epochs
Hidden layer	Output layer				
Log-sigmoid	Log-sigmoid	5–10	0.1–0.9	0.1 –0.9	1,000–7,000
Tan-sigmoid	Linear				

of different network parameters are tabulated in Table 2. The activation functions used in the present study are as follows:

$$f(x) = \frac{1}{(1 + \exp(-\mathrm{ax}))}, \text{(log-sigmoid)} \tag{6}$$

$$f(x) = \frac{(1 - \exp(-ax))}{(1 + \exp(-ax))}, \text{(hyperbolic tangent sigmoid (tan-sigmoid))} \tag{7}$$

$$f(x) = x, \text{(linear)} \tag{8}$$

where a is the slope parameter of the sigmoid function which is considered as one.

The output (y_j) of the jth hidden node is given by

$$y_j = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{9}$$

where x_i's are the input values, n is the number of input nodes, w_{ji} is the weight between ith input node and jth hidden node, and f is the activation function associated with jth hidden node.

The output of the network is derived by

$$d_{\mathrm{se}} = f\left(\sum_{j=1}^{h} w_j y_j\right) \tag{10}$$

where w_j is the weight between the jth hidden node and output unit and h is the number of hidden nodes.

Some training and testing cases of MLP for scour depth prediction around vertical bridge abutment are shortlisted in the Table 3. The shortlisting is done from 330 tested cases of MLP.

The best case of MLP is highlighted in Table 3. It was found with logistic sigmoid transfer function in the hidden as well as in the output layer with Nguyen and Widrow weight initialization method. The selected model of MLP had seven number of neurons in hidden layer, Epoch = 2,500, LR = 0.5, and MC = 0.6. It had very small RMSE during testing, that is, 0.0256, strong correlation value, that is, 0.9829 RMSE, and CC values of the corresponding training case are 0.0249 and 0.9834, respectively. The best case is graphically represented in the Fig. 2.

Table 3 Training and testing results of MLP (Neuron = 7, MC = 0.6)

Epoch	LR	Training		Testing	
		RMSE	CC	RMSE	CC
2,000	0.1	0.0272	0.9807	0.0270	0.9792
	0.2	0.0262	0.9832	0.0259	0.9825
	0.3	0.0264	0.9820	0.0320	0.9694
	0.4	0.0280	0.9792	0.0280	0.9785
	0.5	0.0265	0.9819	0.0340	0.9677
	0.6	0.0292	0.9770	0.0343	0.9662
	0.7	0.0257	0.9820	0.0356	0.9620
	0.8	0.0252	0.9842	0.0337	0.9653
	0.9	0.0263	0.9811	0.0367	0.9697
2,500	0.1	0.0247	0.9841	0.0383	0.9557
	0.2	0.0262	0.9811	0.0340	0.9708
	0.3	0.0310	0.9751	0.0342	0.9673
	0.4	0.0257	0.9825	0.0272	0.9794
	0.5	**0.0249**	**0.9834**	**0.0256**	**0.9829**
	0.6	0.0284	0.9781	0.0308	0.9776
	0.7	0.0280	0.9788	0.0328	0.9734
	0.8	0.0262	0.9815	0.0356	0.9660
	0.9	0.0249	0.9835	0.0322	0.9730
3,000	0.1	0.0278	0.9812	0.0290	0.9746
	0.2	0.0277	0.9792	0.0354	0.9623
	0.3	0.0256	0.9834	0.0257	0.9826
	0.4	0.0264	0.9815	0.0309	0.9719
	0.5	0.0253	0.9840	0.0377	0.9685
	0.6	0.0279	0.9802	0.0361	0.9627
	0.7	0.0276	0.9803	0.0356	0.9642
	0.8	0.0268	0.9809	0.0274	0.9805
	0.9	0.0267	0.9817	0.0347	0.9676

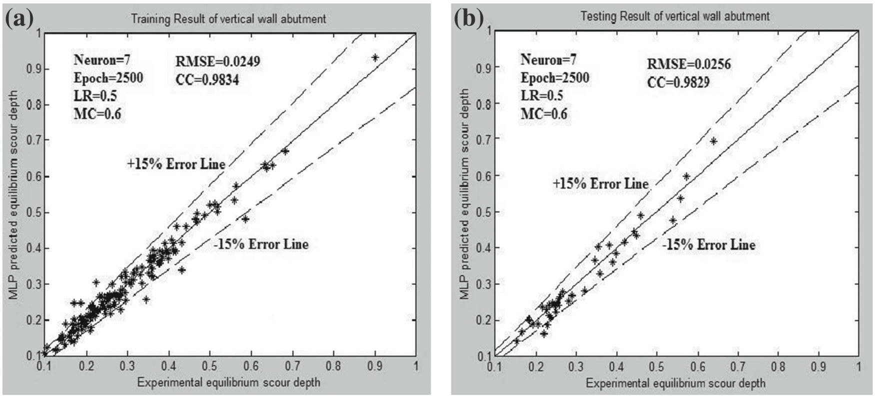

Fig. 2 ANN predicted versus experimental scour depth for vertical wall abutment

Table 4 ANN versus empirical formulae

Method	RMSE	CC
MLP	**0.0256**	**0.9829**
Froehlich [4]	0.1732	0.7047
Kandasamy and Melville [5]	0.0991	0.8802
Melville and Coleman [6]	0.0843	0.9136
Dey and Barbhuiya [7]	0.2078	0.7530

The results of selected MLP model and empirical formulae are tabulated in Table 4. The table shows that the neural network models are capable of predicting scour depth more accurately than the empirical formulae. The performance of MLP is further enhanced by initializing the weights with GA which is discussed in the next section.

6 Weight Optimization Using GA

GAs are computerized search and optimization algorithms based on the mechanics of natural genetics and natural selection [15]. GAs start with a random population of possible solutions to a problem called chromosomes. The individual components within a chromosome are referred to as genes. All chromosomes are then evaluated according to a fitness function. In this study, the average deviation between target and predicted values of scour depth is considered as the fitness function. Once the fitness values are calculated, new chromosomes are created by selecting two chromosomes and applying crossover and mutation operations. The process is repeated until some predefined termination criteria are satisfied [16, 17].

The application of genetic algorithm for weight optimization in MLP consists of three major phases. In the first phase, connection weights of each neuron are represented as gene segments.

In the next step, fitness of these connection weights is evaluated by constructing the corresponding neural network. The inverse of the error function as shown below is considered as the fitness function.

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

where t^p *and* y^p are target and network output for pth training pattern and N is the total number of training patterns.

The third phase is to apply the genetic operators such as selection, crossover, and mutation. The process of selection, crossover, and mutation is repeated until the error is smaller than a predefined value.

The hybrid network learning process consists of two stages: Firstly, GA is employed to search for sub-optimal connection weights for the MLP network. Next,

Table 5 Training and testing results of GA-MLP

Epoch	Training		Testing	
	RMSE	CC	RMSE	CC
170	0.0317	0.9685	0.0351	0.9653
180	0.0292	0.9715	0.0305	0.9697
190	0.0268	0.9796	0.0291	0.9754
200	**0.0203**	**0.9875**	**0.0213**	**0.9864**
210	0.0231	0.9857	0.0239	0.9843
220	0.0218	0.9860	0.0227	0.9851

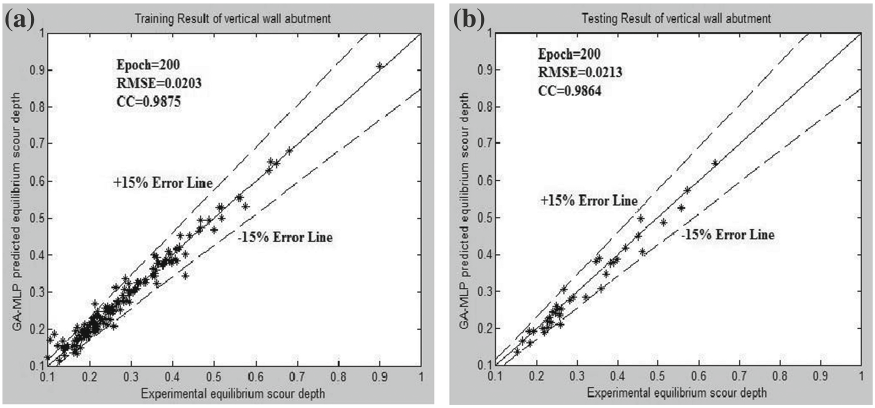

Fig. 3 GA-MLP predicted versus experimental scour depth

MLP with backpropagation algorithm (BP) is used to adjust the final weights. Some training and testing cases are tabulated in Table 5.

From Tables 4 and 5, it is observed that hybrid GA-MLP model provides more accurate result than the empirical as well as MLP model. The best case of GA-MLP is highlighted in Table 5 and graphically represented in Fig. 3. The initial population size was 60, and MLP was run by one iteration for each individual chromosome (i.e., weights). Based on the fitness value, the GA operations were performed and the process is repeated by 80 numbers of times. Finally, MLP was run with BP for 200 iterations. In the above table, epoch represents the number of iterations. MLP was run after applying the GA operations.

7 Conclusion

In the present study, MLP have been implemented to predict the maximum equilibrium scour depth around bridge abutment and found to be suitable for prediction of scour depth around bridge abutment. It is observed that the neural network prediction of scour depth is much more accurate than the existing empirical formulae. The performance of best MLP model has further been improved by combining with GA which performed network connection weight optimization. In the dataset under consideration for vertical wall abutment, the hybrid models provide better result compared to MLP model.

The present study has been carried out using MLP with a single hidden layer and hybrid genetic algorithm-based MLP. Further experimentation needs to be carried out with other soft computing models like neuro-fuzzy model over different datasets.

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