IJCSE International Journal of Computer Sciences and Engineering Open Access
Research Paper Vol.-6, Issue-7, July 2018 E-ISSN: 2347-2693

Genetic Algorithm-Based Neural Network for Estimation of Scour Depth Around Bridge Abutment

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Available online at: www.ijcseonline.org

Accepted: 19/Jul/2018, Published: 31/Jul/2018

***Abstract* —** Scour depth at abutment is a major cause of bridge failure and significant issue towards maintenance cost of a bridge. Thus, early estimation of scour depth at abutment is essential for safe and cost-effective abutment structure design. Extensive research has been carried out to develop methods for predicting the depth of abutment scour. Despite various models presented by researchers to estimate the equilibrium local scour depth, an efficient technique with enhanced estimation capability will be more beneficial. The paper is aimed at investigating the applicability of soft computing (SC) models *viz.* artificial neural network, gene-expression programming (GEP) and hybrid techniques for estimation of scour depth around vertical, semi-circular and 45° wing-wall abutments using laboratory data compiled from published literature. The paper also emphasizes on further enhancement of the performances of the SC based models. On experimentations, the performance of multilayer perceptron (MLP) neural network for each type of abutment was found more effective than radial basis function network, GEP model and empirical equations. The generalization performance of optimal MLP network developed for each type of abutment was then improved with evolving connection weights of the MLP by Genetic Algorithm (GA-MLP). Finally, the hybrid model is validated with different types of validation techniques. The study demonstrates the suitability of the SC based hybrid methodology in improving the predictive accuracy of scour depth around different types of abutments.

***Keywords*—** Scour depth, artificial neural network, genetic algorithm, hybrid technique, GEP

I. INTRODUCTION

Scour around bridge foundation takes place due to the erosion of soil by water stream [1]. Excessive scour may encounter huge maintenance costs or collapses of bridge. Therefore, accurate estimation of the maximum scour depth around abutment and pier is necessary for cost-effective design of bridge foundation. According to a survey report, repairing and maintenance of bridge damage required 50% of total expenditure, out of which 70% was spent to repair abutment scour [2]. Thus, it is essential to estimate reasonably accurate maximum scour depth at bridge abutment for safe and economic design of abutment foundation.

In the recent past, experimental investigation has been conducted and various empirical formulae [3-6] have been developed to predict clear water scour depth around abutments. Each of the developed formulae is suitable to a specific abutment condition and the results of each formula highly differ with each other for the same dataset. Thus, the estimated scour depths using empirical formulae are not reliable due to underestimation or overestimation which may cause bridge failure or increases construction cost.

To enhance the predictive accuracy, data-driven modeling tools based on soft computing (SC) techniques such as artificial neural networks (ANNs) [7-12], adaptive neuro-fuzzy inference system (ANFIS) [13-14], genetic programming (GP) [15-17] and gene expression programming (GEP) [18-20] have been recently employed to estimate scour depth around different types of hydraulic structures. The estimated results with SC methods have been reported to be effectively outperformed the empirical equations.

This paper presents a comparative analysis between MLP, radial basis function (RBF) neural network, GEP and empirical models for predicting scour depth around abutment using the same data set collected from different published literature. The main objective of this study is to enhance the performance of the available SC-based techniques in predicting scour depth around bridge abutment by developing genetic algorithm-based multilayer perceptron (GA-MLP) hybrid computational model. Finally, the performance of hybrid GA-MLP model is compared with the models found more efficient among the aforementioned models.

The remaining contents of this paper are organized as follows: Section II introduces equilibrium scour depth. In section III, development of scour depth estimation models are described. The results obtained are presented in section IV, and section V concludes the paper.

II. Equilibrium Scour Depth around Bridge Abutment

The equilibrium scour depth (d_{se}) around an abutment in uniform sediment can be determined by different parameters such as, average approach flow velocity (U), fluid density (ρ), sediment mass density (ρ_s), acceleration due to gravity (g), abutment length (l), kinematic viscosity (ν), depth of the approach flow (h), median sediments diameter (d_{50}) [6]. Thus, the functional relationship between equilibrium scour depth (d_{se}) at abutment and its dependent parameters can be expressed as:

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

The terms ρ, ρ_s, g and ν can be eliminated from the above equation as they are constant for given sediment and fluid condition. Thus, the Eq. 1 takes the following functional form:

$$d_{se} = f(l, d_{50}, h, U) \quad (2)$$

A pictorial representation of scour at abutment is shown in Fig.1. A detailed review of research related to scour at abutments can be found in [1].

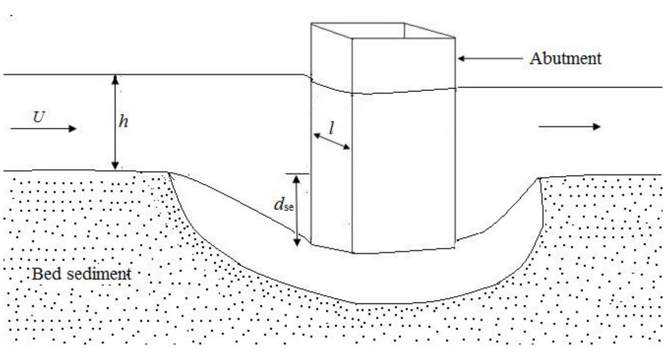


Figure 1. Schematic representation of scour at abutment.

III. Development of Scour Depth Estimation Models

This paper presents the development of different SC models *viz.* ANNs (i.e., MLP and RBF), GEP and GA-MLP for estimation of clear water scour depth around vertical, semi-circular and 45° wing-wall abutments using laboratory data compiled from different literature [6, 21-24].

The dataset used in this study for vertical, semi-circular and 45° wing-wall abutment comprised of four input parameters: abutment length, median grain size, flow depth and average approach flow velocity and one output parameter, i.e. scour depth. The dataset of vertical wall abutment consists of 258 samples after removing nine points as outlier from a total of 267. The sample sizes for semi-circular and 45° wing-wall abutments are 107 and 176 respectively. Table 1 summarizes the ranges of data for each type of abutment.

Table 1. Ranges of experimental datasets

Parameters with unit	Range		
	Vertical Abutment	Semicircular abutment	45° wing-wall abutment
Abutment length (l), m	0.04−0.717	0.04−1.40	0.04−1.38
Sediment size (d_{50}), mm	0.26−18.0	0.26−3.10	0.26−3.10
Flow depth (h), m	0.05−0.60	0.05−0.25	0.02−0.60
Approach flow velocity (U), m/s	0.17−1.54	0.22−0.67	0.20−0.67
Scour depth (d_{se}), m	0.043−0.514	0.053−0.32	0.047−0.74

Each dataset is normalized within 0.1 and 0.9 using (3) to make the training of SC models more effective.

$$x_N = \frac{0.9-0.1}{x_{max}-x_{min}}(x - x_{min}) + 0.1 \quad (3)$$

where, x is the actual value, x_N is the value obtained after normalized of x, x_{max} is the largest and x_{min} is the smallest value in the original dataset. Next, each dataset is divided randomly into training and testing sets consists of 80% and 20% of data points, respectively.

To evaluate the efficiency of the developed SC models, their performances are compared with the empirical formulae [3-6] shown in Table 2.

Table 2. Empirical formulae for scour depth estimation around abutment

Author	Empirical Formula
Froehlich [3]	$\frac{d_{se}}{h} = 0.78 K_s K_\theta \left(\frac{l}{h}\right)^{0.63} F_r^{1.16} \left(\frac{h}{d}\right)^{0.43} \sigma_g^{-1.87} + 1$ where K_s=shape factor of abutment, K_θ = alignment factor of abutment, F_r=approach flow Froude number, σ_g = geometric standard deviation
Melville [4]	$d_{se} = K_{hl} K_I K_{d_{50}} K_s K_\theta K_G$ where K_{hl} reflects the effects of flow depth and abutment length, K_I is the flow intensity factor, K_{d50} correspond to the effects of abutment length and sediment size, K_G signifies the approach channel geometry factor and K_s, K_θ are as defined in the previous equations
Kandasamy & Melville [5]	$d_{se} = K_s K_2 h^n l^{1-n}$ where K_s is the shape factor, K_2 = 5 and n = 1 for h/l <=0.04; K_2 = 1 and n = 0.5 for 0.04 < h/l < 1; and K_2 = 1 and n = 0 for h/l> 1
Dey and Barbhuiya [6]	$\frac{d_{se}}{l} = 7.281 F_e^{0.314} \left(\frac{h}{l}\right)^{0.128} \left(\frac{l}{d_{50}}\right)^{-0.167}$ (for vertical-wall abutment) $\frac{d_{se}}{l} = 8.319 F_e^{0.312} \left(\frac{h}{l}\right)^{0.101} \left(\frac{l}{d_{50}}\right)^{-0.231}$ (for 45° wing-wall abutment) $\frac{d_{se}}{l} = 8.689 F_e^{0.192} \left(\frac{h}{l}\right)^{0.103} \left(\frac{l}{d_{50}}\right)^{-0.296}$ (or semi-circular wall abutment) where F_e is excess abutment Froude number.

The performances of all the models are validated in respect of the statistical measures: mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2). The expressions of these measures are as follows [20]:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left(o_i - t_i\right) \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(o_i - t_i\right)^2} \tag{5}$$

$$R^2 = \frac{\left(\sum_{i=1}^{n}\left(o_i - \bar{o}\right)\left(t_i - \bar{t}\right)\right)^2}{\sum_{i=1}^{n}\left(o_i - \bar{o}\right)^2 \sum_{i=1}^{n}\left(t_i - \bar{t}\right)^2} \tag{6}$$

where, o_i and t_i are predicted output and actual value for the i^{th} input pattern, and $\bar{o}$, $\bar{t}$ are the average over estimated output and observed values, and n is the size of the dataset.

A flowchart of the proposed methodology for developing the SC models to estimate scour depth around bridge abutment is shown in Fig. 2.

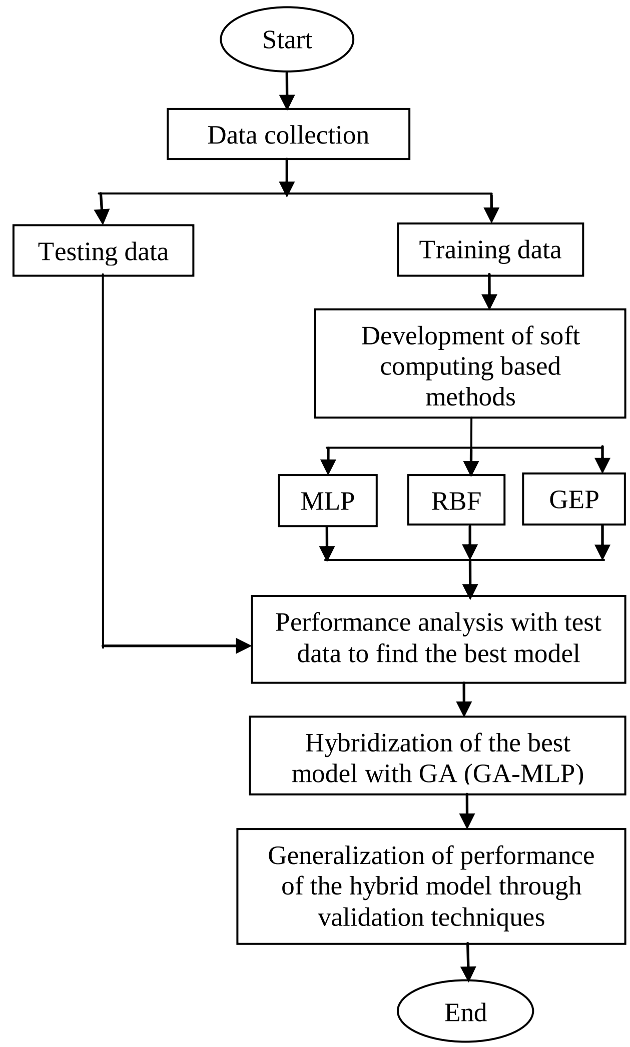


Figure 2. A flowchart of the proposed methodology for developing SC models for estimation of scour depth at abutment

A. Artificial Neural Network

ANNs are universal function approximators, which can map any random input pattern to an output pattern through training. They do not require specifying functional relationship between the dependent and the independent parameters and thus very much suitable in solving complex water resource and hydraulic engineering problems that are often poorly defined. Most of the applications of ANN in hydraulic and water resource engineering involve the use of

MLP and RBF networks. Brief descriptions of these models are presented next.

Multilayer Perceptron network consists of an input layer, one or more hidden layer and an output layer of computational nodes. A diagrammatical representation of the MLP model implemented in this study is shown in Figure 3. A set of data (l, d_{50}, h and U) was provided to the MLP model through the input layer, and subsequently, the network generates an expected result (d_{se}) in the output layer. The network with single hidden layer was trained with Levenberg-Marquardt-Optimization (LMO) algorithm. The LMO algorithm adjusts the weights of each unit to reduce the quadratic error between the actual output and the estimated output [25]. The hidden layer performs the main computational work by extracting meaningful features from the input samples. The number of hidden layer units was determined by trial and error method.

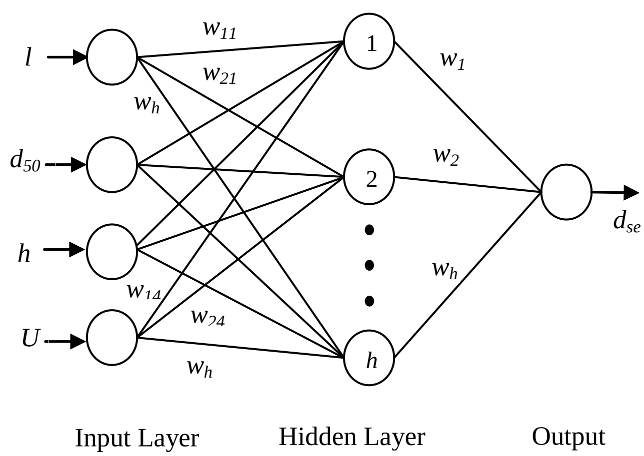


Figure 3. MLP

The networks with 4 to 9 neurons in the hidden layer and initial random weights were trained for 1000-7000 epochs with learning rate and momentum constant values ranging from 0.1 to 0.9. It consist of logistic sigmoid transfer function (7) in the hidden and output layer which was decided based on trails by examining training and testing results simultaneously.

$$f(x) = \frac{1}{1+e^{-x}} \tag{7}$$

In Figure 2, $w_{11}, w_{21}, \ldots, w_{h4}$ are the weights between input and hidden layer, $w_1, w_2, \ldots, w_h$ are weight between hidden and output layer.

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

$$z_j = f\left(\sum_{i=1}^{n} w_{ji} x_i\right) \tag{8}$$

where, x_i is the input value, n represents the number nodes in the input layer, 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 generated by the network is obtained by the following expression:

$$d_{se} = f\left(\sum_{j=1}^{h} w_j z_j\right) \tag{9}$$

where, w_j represents the weight between the output node and j^{th} hidden unit and h specifies the number of nodes in hidden layer.

Radial Basis Function neural network consists of three layers *viz*. an input layer to receive data, a hidden layer and an output layer to produce results. The RBF network employed in the present study contains Gaussian transfer functions in the hidden layer which was trained with random, k-means and fuzzy c-means centre selection methods and pseudo-inverse method for weight initialization between hidden and output layer. Among the aforementioned methods for centre selection, fuzzy c-means method was selected in the RBF network as it produces more accurate results than the other methods for the considered dataset. The schematic diagram of the RBF network with four input parameters *viz*. l, d_{50}, h and U and one output, d_{se} is shown Figure 4.

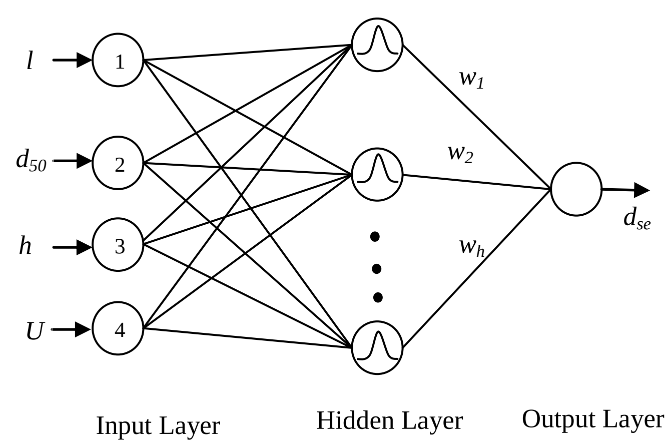


Figure 4. RBF Network

where, w_j represents the weight between j^{th} unit in the hidden layer and the output node.

The values of the input parameters were first fed through the four input node. The output of the j^{th} hidden node is derived from the following expression:

$$\phi_j(x) = \exp\left(-\frac{\left\|x-\mu_j\right\|^2}{2\sigma_j^2}\right) \tag{10}$$

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 RBF model includes linear transfer function in the output layer and thus the output of the RBF model is derived by the following expression

$$d_{se} = \sum_{j=1}^{h} w_j \phi_j(x) \tag{11}$$

B. Gene Expression Programming

GEP is a relatively new evolutionary computing technique proposed by Ferreira [26, 27] is an extension of the GP developed by Koza [28] solves a problem with evolving computer programs. The GEP is a full-fledged genotype/phenotype system with chromosomes consists of one or more genes and each gene encoded as a sub-program. GEP initially generates a random population of probable solutions to a problem called chromosomes of fixed length which are then assessed with a fitness function. Based on the fitness value, chromosomes are selected with roulette wheel selection method and reproduced through genetic operators. The process of selection and genetic modification is repeated until a specified level of accuracy is attained or the specified number of generations is reached. The steps in the GEP development process is briefly discussed below.

In the initial step of GEP development process, a random population chromosome composed of terminal set and function set is generated. In this study, the terminal set contains independent parameters, *l*, d_{50}, *h* and *U* and random floating point numbers between -5 to +5. The basic arithmetic operators (+, -, *, /) and mathematical functions (*exp*, *sqrt*, *power*) were used as the function set. After many number of trials, population sizes of 50, 30, 40 for vertical, semi-circular and 45° wing-wall abutments, respectively were selected as the optimal sizes and then used in the development of GEP models.

Each chromosome is then evaluated with the fitness function which is the inverse of the mean square error (MSE). The fitness (f_i) of i^{th} chromosome can be expressed as

$$f_i = {}^{1}\!/_{MSE_i} \tag{12}$$

The architecture of chromosomes i.e., number of genes in a chromosome and the head, and tail length in each gene were selected in the next step. To evolve solutions to complex problems, it is more appropriate to use multi-gene chromosomes [26]. Thus, in the present study, three genes per chromosomes were chosen by trail method. The head includes functions as well as terminals, and the tail contains terminals only. The head length greater than 10 did not significantly increase the training and testing performance and thus the length of head (*h*) equal to 10 is chosen in the development of GEP model. The tail length (*t*) is a function of *h* and the maximum arity (*n*) of functions and the relationship is *t*=*h**(*n*-1) +1. As the maximum arity of the function set used in this work is 2, the value of *t*=10*(2-1) +1, i.e., *t*=11.

After selecting the architecture of the chromosomes, the linking functions are chosen to link sub-expression trees corresponding to each gene. After experimentation with addition and multiplication as the linking function, the performance of GEP model with addition was found better for the considered problem and thus selected.

In the final step of GEP parameter selection, the set of genetic operators i.e. crossover or recombination, mutation, inversion and transposition and their rate were determined. Table 3 summarizes the parameters of the optimized GEP model for vertical, semi-circular and 45° wing-wall abutments.

Table 3. Parameters of the optimized GEP model

Parameters	**Setting of parameters**		
	Vertical abutment	**Semicircular abutment**	**45° wing-wall abutment**
Population size	50	30	40
Terminal set	*l*, d_{50}, *h*, *U*	*l*, d_{50}, *h*, *U*	*l*, d_{50}, *h*, *U*
Function set	+, -, *, /, *exp*, *sqrt*, *power*	+, -, *, /, *exp*, *sqrt*, *power*	+, -, *, /, *exp*, *sqrt*, *power*
Random constant type	Floating point	Floating point	Floating point
Random constant range	[-5, +5]	[-5, +5]	[-5, +5]
Head length	10	10	10
Number of genes	3	3	3
Linking function	Addition	Addition	Addition
One-point recombination rate	0.15	0.2	0.15
Two-point recombination rate	0.3	0.4	0.35
Gene recombination rate	0.2	0.1	0.2
Mutation rate	0.03	0.03	0.03
Gene transposition rate	0.1	0.1	0.1
Inversion rate	0.2	0.2	0.2

C. Hybrid GA-MLP Network

Backpropagation (BP) learning algorithm is a widely used network learning algorithm but it has a shortcoming of converging to local minima due to gradient search technique.

Genetic algorithm is an effective optimization technique [29] that can be used to optimize initial connection weights in neural network. In this study, a hybrid model of ANN and GA is proposed to initialize and optimize the connection weights of MLP network so as to improve the predictive accuracy of the network for estimating scour depth.

The combination of genetic algorithm in MLP for weight optimization is done by three major steps. In the initial step, chromosomes are considered as weight sets and weights between neurons are considered as gene segments. In step 2, fitness' values are evaluated for these connection weights using (12). This is done by constructing the corresponding neural network with each weight set.

In the final step, application of genetic operators such as selection, crossover and mutation is carried out repeatedly until the goal of accuracy level is acquired or maximum number of iteration is reached.

The hybrid learning process is performed in two stages: Initially sub-optimal connection weights for the network is searched by employing GA. To obtain the sub-optimal weights, GA is run by different number of generations for different types of abutment. In next stage, a final weight adjustment of MLP is done by employing BP algorithm.

One important concern in developing a neural network model is generalization i.e. how efficiently a network can predicts for unseen i.e. new data. ANNs can have either underfitting or overfitting issue. It may happen that the network produce output on training set with a very small error, but the error is large when new data is fed into the network. This happens due to the fact that the network memorized the training samples, but it is not learned enough to generalize new circumstances. The simplest method for generalization of network is hold out method in which data is divided into training and testing sets to train the model and test its performance. There are various other methods for improving generalization performance of network *viz.* early stopping, *k*-fold cross-validation and regularization [30]. In early stopping, data are divided at random into training, validation and testing sets and train various networks using the training set; once error on validation set start increasing, network training is stopped and evaluates the performance with testing set. In *k*-fold cross-validation technique, data are divided randomly into *k* approximately equal distinct subsets. The network is trained with $k-1$ subsets and tested on the remaining subset and the process of training and testing is repeated for a total of *k* times, each time using a different subset for validation. The average performance of the *k* tested cases is considered to evaluate the network. Improving generalization with regularization can be done by modifying the performance measurement function, which is usually selected to be the MSE. This is done by adding a term which contains the mean of the sum of squares of the network weights.

$$Error = \gamma * mse + (1-\gamma) msw \tag{18}$$

where, γ represents the performance ratio, and $msw = \frac{1}{n}\sum_{j=1}^{n} w_j^2$

Although in a very limited number of studies, early stopping was applied on GA-ANN, there is a lack of study on application of other methods to improve generalization performance in hybrid GA-ANN. As generalization approaches are problem dependent, different approaches should be explore, and thus in the present study, hold out, early stopping, cross-validation and regularization techniques are employed in GA-MLP and the comparative analysis of performance with each technique is discussed.

IV. RESULTS AND DISCUSSION

The scour depth estimation models development starts with the development of standalone SC models i.e., MLP, RBF and GEP. The optimal performances in terms of the statistical measures MAE, RMSE and R^2 of the SC models were compared with the considered empirical equations as well as among each other.

In order to verify the applicability and suitability of the proposed hybrid GA-MLP model for estimation of scour depth around abutment, the optimal performance of the hybrid computational model was compared to that of the MLP, RBF and GEP.

A. Comparison of ANNs and GEP models with empirical equations

To compare the performances of the MLP, RBF and GEP model, the optimal cases of each model was identified. The model configuration having minimum MAE, RMSE and maximum R^2 values between target and predicted values during testing were selected as optimal. The performance indices values of these optimal SC models along with that obtained with the empirical formulae for vertical, semicircular and 45° wing-wall abutment are tabulated in Table 4-6.

Table 4. Comparison of ANNs, GEP and empirical formulae for vertical wall abutment

Method	Training			Testing		
	MAE	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**
Froehlich [3]	0.1235	0.1864	0.2272	0.0972	0.1680	0.2521
Melville [4]	0.0903	0.1278	0.5597	0.0971	0.1378	0.5366
Kandasamy and Melville[5]	0.1158	0.1457	0.5284	0.0865	0.1137	0.5649
Dey and Barbhuiya [6]	0.0972	0.1442	0.4749	0.0857	0.1321	0.4517
GEP	0.0129	0.0176	0.8810	0.0135	0.0189	0.8590
MLP	0.0085	0.0125	0.9318	**0.0109**	**0.0154**	**0.9310**
RBF	0.0116	0.0157	0.8947	0.0117	0.0168	0.8815

Table 5. Comparison of ANNs, GEP and empirical formulae for semicircular abutment

Method	Training			Testing		
	MAE	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**
Froehlich [3]	0.0876	0.1102	0.4508	0.1624	0.2103	0.2417
Melville [4]	0.0397	0.0486	0.6556	0.1038	0.1334	0.2775
Kandasamy and Melville[5]	0.0489	0.0675	0.4951	0.0613	0.0829	0.4341
Dey and Barbhuiya [6]	0.0124	0.0195	0.8651	0.0205	0.0318	0.7080
GEP	0.0062	0.0094	0.9752	0.0102	0.0196	0.9157
MLP	0.0028	0.0043	0.9956	**0.0067**	**0.0150**	**0.9432**
RBF	0.0041	0.0063	0.9892	0.0096	0.0152	0.9386

Table 6. Comparison of ANNs, GEP and empirical formulae for 45° wing-wall abutment

Method	Training			Testing		
	MAE	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**
Froehlich [3]	0.0716	0.0869	0.5078	0.0941	0.1548	0.4714
Melville [4]	0.0384	0.0558	0.6140	0.0490	0.0584	0.6036
Kandasamy and Melville[5]	0.0957	0.1326	0.4836	0.0628	0.0851	0.5592
Dey and Barbhuiya [6]	0.0312	0.0534	0.5800	0.0315	0.0459	0.6500
GEP	0.0083	0.0107	0.9522	0.0116	0.0145	0.9361
MLP	0.0036	0.0059	0.9948	**0.0051**	**0.0072**	**0.9833**
RBF	0.0058	0.0073	0.9708	0.0054	0.0074	0.9819

As shown in the above tables, the low values of MAE, RMSE and high values of R^2 of SC models compared to the empirical equations indicate that the SC models are able to estimate scour depth much more precisely than the empirical formulae for all the three types of abutments. From Table 4-6, it is also observed that ANN models outperform GEP for all the three types of abutments. Moreover, MLP is found more effective than RBF in predicting scour at abutment for the considered dataset.

It may also be observed from Table 4-6 that the performances of SC models in predicting scour depth at vertical wall abutment is inferior to their performance for other two types of abutment. This is due to the fact that the dataset for scour around vertical wall abutment was collected from more number of sources than the other type of abutments, and thus more diverse than the other sets.

B. *Comparison of GA-MLP and ANN models*

As the performance of MLP was found better, it was considered for further enhancement by developing hybrid GA-MLP model. To compare the performance of GA-MLP with MLP, the best testing cases of both the models along with the corresponding training cases for each type of abutments are tabulated in Table 7.

Table 7. Comparison between GA-MLP and MLP

Abutment type	Method	Training			Testing		
		MAE	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**
Vertical	GA-MLP	0.0082	0.0114	0.9514	**0.0105**	**0.0139**	**0.9374**
	MLP	0.0085	0.0125	0.9318	0.0109	0.0154	0.9310
Semi-Circular	GA-MLP	0.0034	0.0052	0.9936	**0.0063**	**0.0140**	**0.9618**
	MLP	0.0028	0.0043	0.9956	0.0067	0.0150	0.9432
45° Wing-wall	GA-MLP	0.0029	0.0041	0.9952	**0.0040**	**0.0055**	**0.9855**
	MLP	0.0036	0.0059	0.9948	0.0051	0.0072	0.9833

Table 7 shows that the performance of GA-MLP is more effective than MLP during testing i.e. for unseen data for all the three types of abutments. The scatter diagrams of observed equilibrium scour depth versus GA-MLP predicted values along with performance indices for all the three types of abutments are shown in Figure 5.

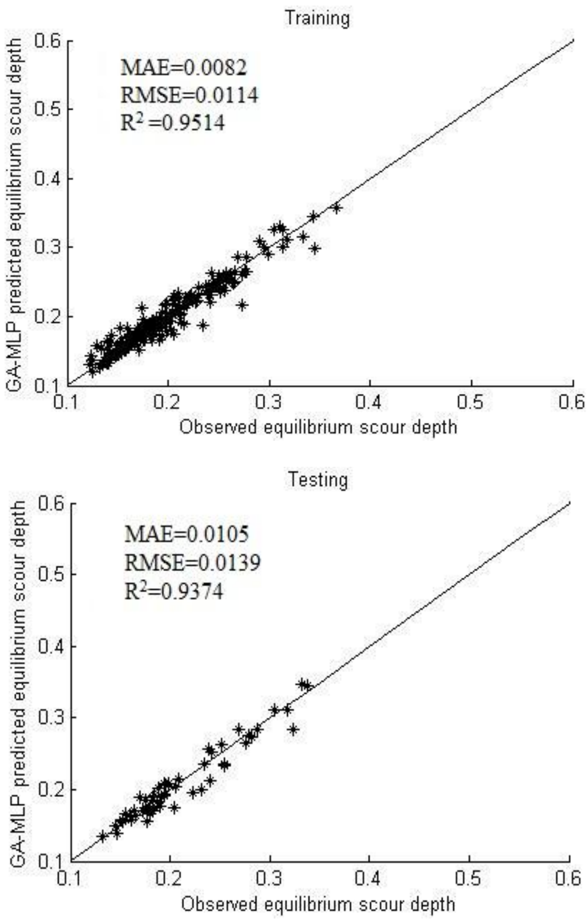
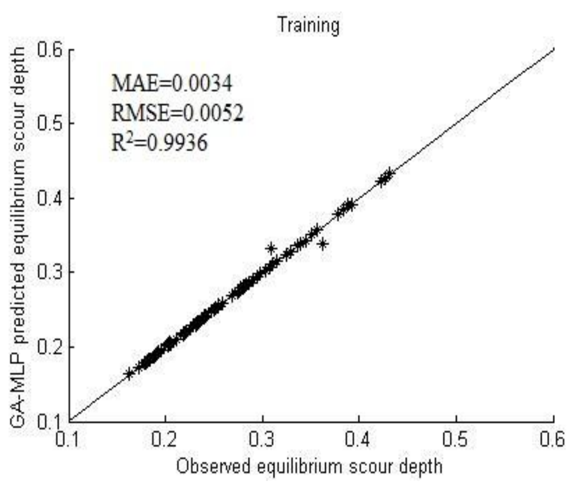


Figure 5 (a) Observed versus GA-MLP predicted scour depth for vertical wall abutment



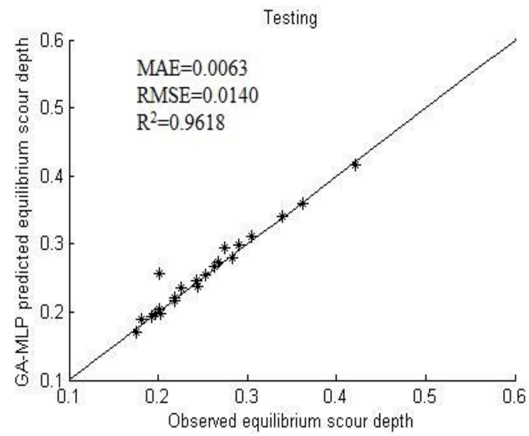


Figure 5(b) Observed versus GA-MLP predicted scour depth for semicircular wall abutment

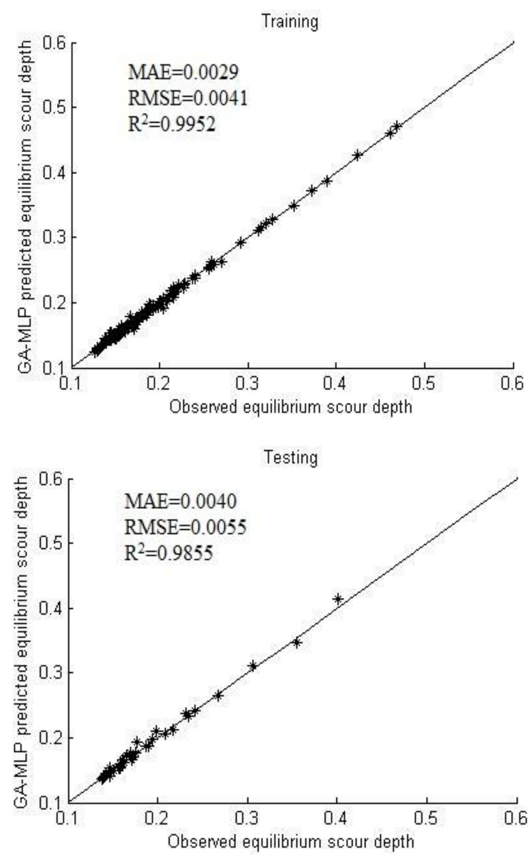


Figure 5(c) Observed versus GA-MLP predicted scour depth for 45° wing-wall abutment

The above figures illustrate the performances of the proposed GA-MLP model validated with holdout method. R^2 value of 0.9374, 0.9618 and 0.9855 with testing dataset of vertical, semicircular and 45° wing-wall abutment and MAE=0.0105, RMSE=0.0139 for vertical wall abutment, MAE=0.0063, RMSE=0.0140 for semi-circular wall abutment and MAE=0.0040, RMSE=0.0055 for 45° wing-wall abutment during testing indicate that the GA-MLP model provide reasonably acceptable results.

The generalization performance of the hybrid model is further improved by employing different techniques such as, early stopping, cross-validation and regularization. Some of the generalization performances of GA-MLP for each type of abutment with different approaches are tabulated in Table 8 – 10. The "epoch" in the tables represents the number of BP runs, after obtaining suboptimal weights with GA.

Table 8. GA-MLP Training and Testing Results for vertical wall abutment

Epoch	Training			Testing		
	MAE	**RMSE**	R^2	**MAE**	**RMSE**	R^2
Early stopping						
741	0.0169	0.0237	0.8571	0.0164	0.0229	0.8562
794	0.0152	0.0209	0.8642	0.0175	0.0251	0.8471
836	0.0116	0.0174	0.8780	0.0189	0.0276	0.8345
Regularization						
900	0.0117	0.0178	0.8720	0.0123	0.0187	0.8681
1000	0.0110	0.0165	0.8774	0.0116	0.0176	0.8767
1100	0.0124	0.0183	0.8658	0.0134	0.0195	0.8608
k=5 fold cross validation						
1000	0.0098	0.0129	0.9278	0.0108	0.0131	0.9362
1100	0.0087	0.0118	0.9425	**0.0095**	**0.0125**	**0.9444**
1200	0.0076	0.0107	0.9436	0.0115	0.0136	0.9306

Table 9. GA-MLP Training and Testing Results for semicircular wall abutment

Epoch	Training			Testing		
	MAE	**RMSE**	R^2	**MAE**	**RMSE**	R^2
Early stopping						
553	553	553	553	553	0.0229	0.8562
601	601	601	601	601	0.0251	0.8471
678	678	678	678	678	0.0276	0.8345
Regularization						
600	600	600	600	600	0.0187	0.8681
700	700	700	700	700	0.0176	0.8767
800	800	800	800	800	0.0195	0.8608
k=5 fold cross validation						
700	700	700	700	700	0.0131	0.9362
800	800	800	800	800	**0.0125**	**0.9444**
900	900	900	900	900	0.0136	0.9306

Table 10. GA-MLP Training and Testing Results for 45° wing-wall abutment

Epoch	Training			Testing		
	MAE	**RMSE**	R^2	**MAE**	**RMSE**	R^2
Early stopping						
636	0.0067	0.0138	0.9222	0.0065	0.0134	0.9256
684	0.0063	0.0126	0.9308	0.0062	0.0121	0.9477
739	0.0062	0.0114	0.9510	0.0061	0.0112	0.9537
Regularization						
800	0.0097	0.0159	0.8979	0.0068	0.0149	0.9107
900	0.0092	0.0133	0.9160	0.0064	0.0142	0.9185
1000	0.0094	0.0140	0.9378	0.0063	0.0137	0.9235
k=5 fold cross validation						
900	0.0053	0.0088	0.9557	0.0043	0.0063	0.9677
1000	0.0048	0.0071	0.9716	**0.0038**	**0.0049**	**0.9870**
1100	0.0041	0.0064	0.9685	0.0040	0.0056	0.9845

Table 8 – table 10 indicate that the *k*-fold cross validation is more effective compared to early stopping and regularization for the considered dataset. From the above tables, it is found that GA-MLP with *k*-fold cross validation yields R^2 value of 0.9444, 0.9641 and 0.9870 for the testing dataset of vertical, semicircular and 45° wing-wall abutment. It indicates that 94.44%, 96.41% and 98.70% total variations of scour depth predicted by GA-MLP for unknown situation of vertical, semicircular and 45° wing-wall abutment can be explained by the linear relation between the target and predicted values. GA-MLP with small error values of MAE=0.0095, RMSE=0.0125 for vertical wall abutment, MAE=0.0062, RMSE=0.0134 for semi-circular wall abutment and MAE=0.0038, RMSE=0.0049 for 45° wing-wall abutment on testing dataset also confirms the acceptable generalization performance of the proposed model. Therefore, GA-MLP with *k*-fold validation may be considered as an addition to the scour depth estimation methodologies.

C. Sensitivity Analysis

To find out the relative influence of each of the affecting parameters on scour depth, sensitivity analysis was carried out with the trained hybrid model. This was done by eliminating one of the independent factors from (2) at a time. The results of the sensitivity tests for vertical, semicircular and 45° wing-wall abutment are summarized in Table 11.

Table 11. Sensitivity analysis

Method	Vertical			Semicircular			45° wing-wall		
	MAE	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**	**MAE**	**RMSE**	**R^2**
GA-MLP with l, d_{50}, h, and U	0.0105	0.0139	0.9374	0.0063	0.0140	0.9617	0.0040	0.0055	0.9855
GA-MLP without l	0.0394	0.0585	0.7941	0.0224	0.0357	0.8213	0.0187	0.0256	0.8336
GA-MLP without d_{50}	0.0158	0.0206	0.9140	0.0117	0.0195	0.9482	0.0079	0.0138	0.9217
GA-MLP without h	0.0213	0.0327	0.8677	0.0168	0.0226	0.8971	0.0092	0.0167	0.9010
GA-MLP without U	0.0236	0.0361	0.8624	0.0196	0.0272	0.8788	0.0126	0.0193	0.8678

From the sensitivity analysis it is observed that when the abutment length was removed, maximum error and minimum coefficient of determination was given by the model. Thus, abutment length has maximum affect on scour depth and is considered as more sensitive than the other parameters. It is also observed that sediment size has least effect on scour depth.

V. Conclusion and Future Scope

The application of the SC methods such as, ANNs (i.e. MLP and RBF), GEP and hybrid GA-MLP to estimate local scour at vertical, semicircular and 45° wing-wall abutment in clear-water condition is presented in this paper. The application of GA-MLP and comparison with ANN and GEP carried out in this study is another significant addition to scour-depth estimation methodologies for abutments. The results obtained in the study demonstrate the suitability of SC models in scour depth estimation at bridge abutment. It is found that the scour depth prediction with SC models is much more accurate than the existing empirical methods. It is also observed that the performances of ANNs are more effective than GEP. Moreover, MLP outperforms RBF network for the considered dataset. The performance of the MLP model is further been enhanced by combining with GA, which optimizes connection weights. By comparing the generalization performance of the GA-MLP with early stopping, *k*-fold cross-validation and regularization, *k*=5 fold cross validation is found more efficient. Thus, GA-MLP with *k*-fold cross-validation method may be recommended as an efficient approach for the prediction of scour depth around abutment. With sensitivity analysis, abutment length is found most sensitive while median grain size is found least sensitive.

The research work carried out in this study contributes to the development of the expert systems for efficient estimation of maximum scour depth for constructing safe and economic bridge foundation. While a significant progress in the enhancement of SC methods for scour depth estimation is made, the developed models may be further enhanced by appropriate adjustment of the algorithmic framework of the techniques. Although, the developed model is efficiently predicting scour depth, observations and availability of more experimental data will be beneficial for the development of more generalized models and validation with field observations will be more effective for practical purpose.

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