Asia-Pacific Journal of Science and Technology :Volume: 26 .Issue :02. Article ID :.APST-26-02-16. Research Article

APST

Asia-Pacific Journal of Science and Technology

https//:www.tci-thaijo.org/index.php/APST/index

Published by the Research and Graduate Studies,
Khon Kaen University, Thailand

Survey the suitable approach to predict the local scour depth around a bridge pier

Waqed H. Hassan [1,*] and Halah K. Jalal[1]

[1]Department of Civil Engineering, University of Kerbala, Kerbala, Iraq
[*]Corresponding author: waaqidh@uokerbala.edu.iq

Received 18 December 2020
Revised 30 March 2021
Accepted 1 April 2021

Abstract

Local scouring around the piers of bridges is one of the main reasons for bridge failure. The main purpose of this study was to survey the suitable empirical equation to predict local scour depth around pier bridges, by applying various approach techniques to achieve more effective predictions. These approaches include gene expression programming (GEP), artificial neural networks (ANN) and statistic non-linear regression (NLR) methods. The empirical equations derived were based on shape of pier, intensity of flow, flow depth ratio, pier width ratio and attack angle. The data set, a total of 729 data points obtained from numerical simulations using Flow-3D, were divided into training and validation datasets (test). A functional relationship was created using GEP, its performance compared to ANN and NLR. Identification of the best techniques to predict scour depth, was achieved using three statistical parameters: R^2, RMSE and MAE. The equation obtained using GEP, performed better than the conventional regression NLR model, but slightly poorer than that of ANN (R^2 = 0.89, RMSE=0.152 and MAE= 0.118). Even though ANN performed better than GEP (R^2 = 0.93, RMSE=0.129 and MAE=0.088), the latter is preferred because of its ability to provide compressed and explicit arithmetic expressions. The GEP model equation has been verified with laboratory data, predicting a good result.

Keywords: Scour depth prediction, Gene expression programming (GEP), Artificial neural network (ANN)

1. Introduction

Among the most important issues related to the management of rivers is the matter of river flow, this including flooding, transportation of sediments, deformation of the riverbed and scouring. One of the major causes of bridge failure is scouring, besides overload and impact, resulting in huge loss of life and severe economic impact [1]. The scour that may occur at bridge sites generally consists of three elements; general scour, local scour and contraction scour. Local scouring is the result of down-flow at the top of the pier and the subsequent horseshoe vortices that form at the base of the scour hole. Down-flow reaches the bottom of the channel and moves sediment away from the base of the pier, creating a scour hole. When the down-flow reaches the bottom of the channel, it interacts with the incoming flow, a complex vortex system developing. As the scour develops, an increase in the depth of flow reduces the horseshoe vortex force in the bed, resulting in a decrease in scour rate before reaching equilibrium [2,3]. Riverbed deformation is of key interest to infrastructure and hydraulic engineers as the presence of hydraulic structures such as bridges, cause flow contraction and scouring around piers and abutments [4]. A number of studies having developed methodologies and techniques to analyze scour depth through experimental testing e.g., [5]. Most of these tests have been carried out on larger bridges because they are very expensive need more maintenance. However recently, Computational Fluid Dynamics (CFD), which discretizes and solves Navier-Stokes and mathematical continuity equations, has been applied to a wide range of flow process numerical simulations. As a consequence, much research has adopted numerical simulation methods for scouring e.g. [6], all of whom have evolved three dimensional models to simulate local scour at bridge piers. The primary purpose of using numerical simulations is that instead of designing a large model and using expensive tools to measure specific variables, basic fluid behavior including velocity distribution, turbulent kinetic energy, bed shear and pressures, can be obtained through the application of CFD programs [3].

Large bridges cost billions of dollars, this justifying rigorous scour depth prediction, both for safety and economic reasons as under- or over-predicted scour depth may lead to bridge failure or costly bridge construction [7]. While there remains a great deal of uncertainty and controversy regarding scour prediction, it can be suggested that most bridge failures have resulted from a lack of detailed knowledge regarding the problem of scouring. Scientific research is required at a local level before a universal formula for a particular location can be produced with confidence but there are relatively few records about scouring specific bridges, these limiting comparisons to information obtained from different prediction methods. In addition, many methods have been developed to estimate the depth of scouring necessary as said mechanism is complex making it difficult to create a common empirical model to predict the depth of scour under various field conditions such as intensity of flow, pier width ratio, flow depth ratio, pier shape and angle of attack. Most predictive formulas identified from the literature, have been developed using a traditional regression-based mechanism using field and experimental data [8]. More recently, [9] reported that Colorado State University (CSU) [10] have provided sensible predictions, while [11] and [12] equations over-predict scour depth, this dependent on the comparison of the scour equation of the bridge pier using both laboratory and field data. Some of the researchers above developed their formulas using dimensional analysis followed by non-linear analysis regression, but this process is not very accurate and includes lengthy computations. Because this approach is currently less attractive, a large number of studies have emerged which apply soft computational skills using artificial intelligence (AI) techniques so that modeling can be executed easily and accurately carried out [13-15].

Inductive modeling techniques based on artificial intelligence, are used extensively to simulate complicated response functions including scour analysis because of their robust non-linear model structures and ability to capture the cause-and-effect relationship of these processes. These artificial intelligence-based technologies consist of adaptive neuro-fuzzy inference systems (ANFIS), artificial neural networks (ANNs), genetic programming (GP), genetic algorithms (GA) and Gene Expression Programming (GEP) [16,17]. For hydraulic design issues as in the case of nonlinear and highly complicated response functions, ANN has been reported to provide reasonably good solutions [18]. GEP's soft computing tool has recently been recognized as superior to many of the other available tools due to ease of coding, simple modeling and quick calculations. Numerous researches across a range of fields of engineering, has shown that GEP is also more accurate and practical than other previously recommended techniques [13].

In the literature, it was noted that the mathematical analysis of depth of scour depends on artificial intelligence technologies in general and GEP in particular, but that these have not been widely implemented implying that there is an immediate need to do this work. Therefore, this study's main objectives are an examination of the performance of the proposed GEP model compared to ANN and NLR models.

2. Materials and methods

Three modeling techniques, GEP, ANN and NLR were used to develop a new scour depth formula to predict the depth of local scouring at the pier of the bridge. Five dimensionless parameters, obtained by dimensional analysis, were selected as the influencer parameters on the depth of scour: intensity of flow, pier width ratio, flow depth ratio, pier shape and angle of alignment (attack), these used as the input and output parameters for GEP, ANN and NLR modeling. The data obtained from Jalal's (2019) [19] numerical model was used in the calibration (training) and verification (testing) processes for the three proposed models. The selected data has been measured in the laboratory of Kerbala University, Iraq. Identification of the best techniques to predict scour depth was achieved by using three statistical parameters: R^2, RMSE and MAE. Sensitivity analysis was also conducted to determine the influence of each input parameter on the predicted scour depth to identify the most sensitive parameter.

2.1 Local scouring around the pier of a bridge: dimensional analysis

The local scouring depth around the pier of a bridge under a steady flow, above a bed of uniform and non-cohesive sediments and with clear water conditions (Figure 1), depends on a number of parameters: flow variables, fluid variables, bed sediment variables, pier variables, flume geometry and time. Scour depth (ds) in straight channels having homogeneous sediment can be expressed as follows [12]:

$$ds = f(\rho, \nu, V, y, g, \rho_s, d_{50}, \sigma g, V_c, B, b, L, K_s, K\theta, t) \quad (1)$$

Where ds represents the maximum depth of scour, ρ density of fluid, ν kinematic viscosity of the fluid, V approach velocity, y depth of flow, g gravitational acceleration, ρ_s sediment density, d_{50} median sediment size, σg standard deviation of the distribution of the particle size, Vc critical mean approach flow velocity, B channel width, b diameter of the pier, L length of pier, K_s shape factor of the pier (these including circular, rectangular, square, elliptical, oblong, octagonal, hexagonal, ogival and lenticular), $K\theta$ correlation coefficient of flow alignment and t duration of flow.

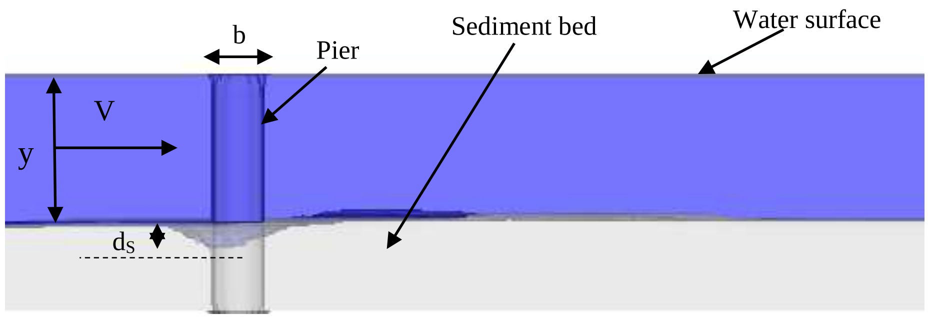

Figure 1 Flow and local scouring around a circular bridge pier.

The physical mechanism of local scour around a bridge pier can be better understood if appropriate dimensionless parameters describing the phenomenon are identified so some of these parameters are disregarded in this study due to the huge amount of data. One layer of sediment ($d_{50} = 0.385\ mm$) was used throughout this study, with a uniform gradient and time of flow (t=30 min.) meaning that the terms d_{50}, σg and t are not required. In Equation (1), the dimensional analysis of the fifteen independent parameters is reduced to five dimensionless parameters using Buckingham's hypothesis, selecting ρ, V, and b as the iterative parameters. The function that describes the influence of these parameters on scour depth can be written as:

$$\frac{d_s}{b} = f\left(K\theta\ , \frac{y}{b}\ , K_s\ , \frac{B}{b}\ , \frac{V}{V_c}\right) \tag{2}$$

Where $\frac{d_s}{b}$ represents the ratio of scour depth, $\frac{y}{b}$ flow depth ratio, $\frac{B}{b}$ pier width ratio and $\frac{V}{V_c}$ flow intensity. Dimensionless parameters in Equation (2) were used for GEP, ANN, and NLR modeling as input and output parameters.

2.2 Flow-3D modelling

Flow-3D is a computational fluid dynamic (CFD) package manufactured by Flow Science Inc. Flow-3D uses numerical techniques developed specifically to solve fluid motion equations resulting in transient 3D solutions to physical problems and multi-scale flow (Flow-3D manual, 2014). It can examine the conduct of gases and liquids specific to transient problems, free surface and transient sediments. 3D Navier-Stokes' equations are solved by using a nonhydrostatic finite difference model, the purpose of numerical simulations by Flow-3D to design an accurate model of fluid and sediment flow around a bridge pier [19,20].

2.3 Data set obtained from numerical simulation

To calibrate and validate the effectiveness of Flow-3D modelling, the results generated by the [21] experimental model, have been compared with the numerical simulation results obtained by Flow-3D. The error rate of the maximum scour depth was equal to 10%, this indicating a good fit between experimental and numerical work, the numerical simulation successfully reproducing the depth of scour around the bridge pier [13].

729 data points generated via the numerical simulation of the bridge pier scour depth around different pier shapes [19], were divided randomly into two groups: 80% used to generate the model, the other 20% used to validate it.

Table 1 summarizes the range of parameters. This data set were modelled using GEP, ANN and NLR to develop theoretical model to predict the relative maximum depth of scour (ds/b) around the pier of bridge and to identify the most appropriate techniques to estimate the scour depth by using three statistical parameters: R^2, RMSE and MAE. The methodology for this study is shown in Figure 2.

Table 1 Minimum and maximum values of data used in the training and testing of GEP, ANN, and NLR.

Parameters	Data limits	
	Minimum	Maximum
V/V_c	0.55	1.00
y/b	0.20	2.95
b/B	0.11	0.15
Ks	0.71	1.26
Kθ	1.00	1.68
ds/b	0.00	1.88
y: cm	5.00	15.00
b: cm	5.08	6.85
B: cm	45.60	45.60
V: cm/s	18.00	32.80
θº	0.00	45.00

Where: V/V_c: flow intensity; y/b: flow depth ratio; b/B: pier width ratio; Ks: pier shape factor; Kθ: correlation coefficient of flow alignment; ds/b: scour depth ratio; y: depth of flow (cm); b: pier diameter or pier width (cm); B: channel width (cm); V: approach flow velocity (cm/s); θ: angle of flow alignment (º).

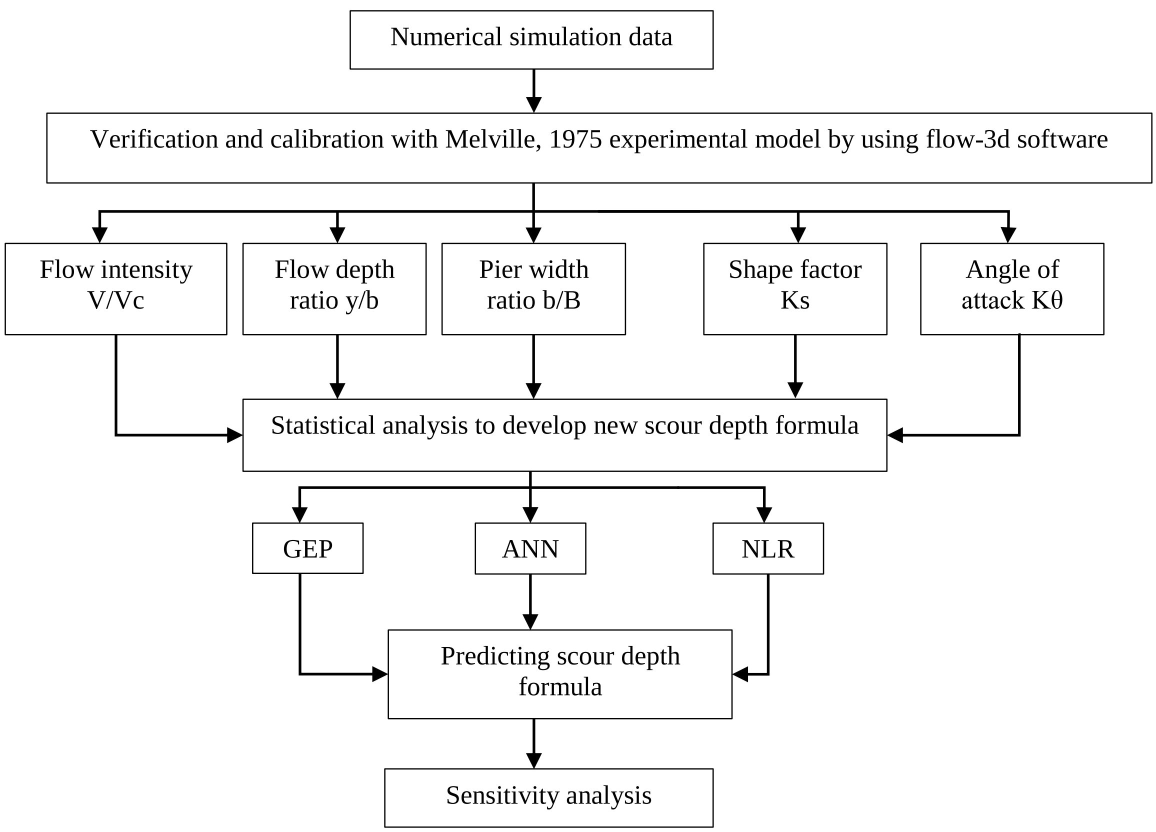

Figure 2 Flow chart of the research methodology.

2.4 *Overview of GEP and ANN*

2.4.1 GEP

GEP is a new technology based on evolutional Artificial Intelligence (AI), improved by [22]. It is a stretch of genetic programming (GP) improved by [23] which includes both simple linear chromosomes of constant length (genomes), similar to those used in GAS, and branching constructs of various shapes and sizes formulated as expression trees (ETs) in a phenotype form, similar to analysis trees in GP. In its current form, it integrates the benefits of both its ancestors, GP and GA, with some of the limitations of these technologies removed [24]. The major goal of this system is to create a mathematical formula which can be adapted to the data set provided to create a GEP model. The GEP process for this mathematical equation comprises a figurative regression via most of the genetic factors for GA.

The GEP operation begins with the random generation of chromosomes for a specific individual number (the initial population). Each of these individual chromosomes is then evaluated by using a fitness function against a set of fitness cases [25]. The choice of chromosomes then depends on the fitness value: those with a better 'goodness of fit' have a greater chance of being selected for the next generation.

2.4.2 ANN

An artificial neural network (ANN) is defined as a flexible mathematical structure capable of characterizing non-linear and complex relationships between input and output data sets. ANN models are effective and useful, especially with problems where it is difficult to describe the properties of processes using physical equations [26,27]. ANNs can be used to estimate local scouring depth by constructing a multilayered, feed-forward network. Random mapping between input and output vectors provides three essential layers of neurons; input, hidden and output, each neuron acting as an independent computational component. ANNs have a high degree of freedom associated with their architecture, this feature providing strength to the model. Before application, the neural network learns using datasets, this giving the network input-output pairs and values of contact weights, centers or bias [28]. The structural layers of ANN are illustrated in Figure 3.

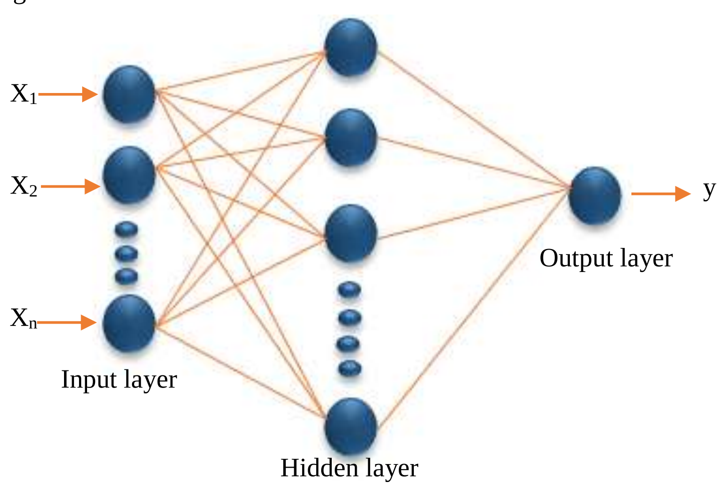

Figure 3 The structural shape of ANN [19].

Each input layer cell (first layer), takes the input data for each separate parameter (variable). Each entry is multiplied by the corresponding weight, the result then transferred to the next cell in the second layer (hidden layer) where a suitable transformation function (activation) is applied. By multiplying the output of each cell in the hidden layer by the weight of the corresponding contact between the hidden and output neurons, the outcomes are transferred from the hidden layer (second layer) to the output layer. The final layer produces the output of the neural network for additional data treatment.

2.5 Modeling of the depth of local scouring around a bridge pier

2.5.1 GEP Model

729 datasets representing bridge pier scour depth, were obtained from the numerical simulation of the bridge pier using Flow-3D software. This data is represented in Equation (2), the parameters $K\theta$, $\frac{y}{b}$, K_s , $\frac{B}{b}$, $\frac{V}{V_c}$, considered independent input parameters, the local scour depth ratio ($\frac{d_s}{b}$) used as a dependent output parameter. A model of the output variable ($\frac{d_s}{b}$) was developed using GEP. These datasets were divided into training and validation/testing datasets. 583 observations (approximately 80%) were chosen at random and used for training to build the GEP model. The testing / validation set containing 146 data points (approximately 20%), was used to validate/test the GEP model. After dividing the data, various parameters for model construction were identified, these illustrated in the following six steps:

- Step one: GEP begins with an initial group of individuals. An individual population consists of chromosomes of fixed length which may be single or multi gene. In the initial population, any size of population can be used, but chromosomes within the range 30 to100 have provided better results in the past [21]. After enough trials to determine the optimum size of population required to produce acceptable results, the population selected for this model was 50 chromosomes.
- Step two: each individual is evaluated, their fitness function calculated using RMSE.
- Step three: for each gene in the chromosome, the set of function (F) and the set of terminals (T) are defined. This model is designed by using essential computational operators and power, thus giving F = {+, -, *, /, power}. The terminal sets, including the independent variable and random numerical constant, gave T = { $K\theta$, $\frac{y}{b}$, K_s , $\frac{B}{b}$, $\frac{V}{V_c}$, ?} where '?' represented the random numerical constant (RNC).
- Step four: the structural arrangement of the chromosomes is represented in this step to determine the number of genes and length of their heads. This begins by using a single gene and gradually increasing it. According to [21], the success rate increases as the number of genes in a chromosome increases from one to three. Therefore, in each chromosome, three genes were used making it multigenic, the head equal to eight (h=8). To represent the random numerical constants (D_C), five random, floating-type digital constants were identified for each gene in the range -10 to +10.
- Step five: this step comprises selection of the linking function. Since there are three genes, the results can be generated from three different sub-ETs (Expression trees). These sub-ETs are bound by addition operators (+), to obtain the final solution.
- Step six: Finally, the set of genetic factors that cause differences and rates their values were chosen. A mixture of all genetic factors such as mutation, inversion, transposition (RIS, IS and genetic transposition), D_c -specific genetics and recombination (gene recombination, one-point and two-point) were used. A rate of 0.044 of two, one-point mutations was used. The other genetic operator rates are listed in Table 2.

Table 2 Parameters of the GEP model for the scour depth around a bridge pier.

Parameters	Values
Population size	50
Set of function	+, -, *, /, power
Set of terminals	$K\theta, \frac{y}{b}, K_s, \frac{B}{b}, \frac{V}{V_c}$, ?
Random numerical constant (RNC)	05
RNC type	Floating point
Range of RNC	[-10, 10]
Length of head	08
Number of genes	03
Linking function	+
Fitness function	RMSE
Rate of mutation	0.044
Rate of inversion	0.1
Rate of IS transposition	0.1
Rate of RIS transposition	0.1
Rate of Gene transposition	0.1
Rate of One-point recombination	0.1
Rate of Two-point recombination	0.3
Rate of Gene recombination	0.3
Rate of Dc-specific mutation	0.044
Rate of Dc-specific inversion	0.1
Rate of Dc-specific IS transposition	0.1
Rate of Random constant mutation	0.01

The maximum fitness function is the termination standard (RMSE). The software was operated for a number of generations and was stopped when there was no further development in the value of the fitness function or statistical coefficients, or when the model reached maximum fitness function (maximum fitness 1000). There was no significant change after 324365 generations. Subsequently, and after over 10 trials, the maximum fitness function (RMSE) of the ds/b for training and validation were 868.82 and 859.33, respectively. The scour depth (ds/b) equation is a function of the expression tree (ET) (Equation 3). The corresponding expression tree language is illustrated in the Figure 4.

The scour depth (ds/b) formula is:

$$\frac{ds}{\mathrm{b}} = d2 * \left(\frac{\frac{d1}{d0} + \frac{d4}{d1}}{d0 + d1 - 7.38}\right) + (d0 * d2) * [2.66 * d3 + d1 + 2.66 * d4] + d2 - \left[\left((d1^{d0} * d2) + \frac{d0}{d1}\right) * d2\right] \quad (3)$$

The definition of the parameters used in Equation 3 and in the ETs, are represented in Table 3.

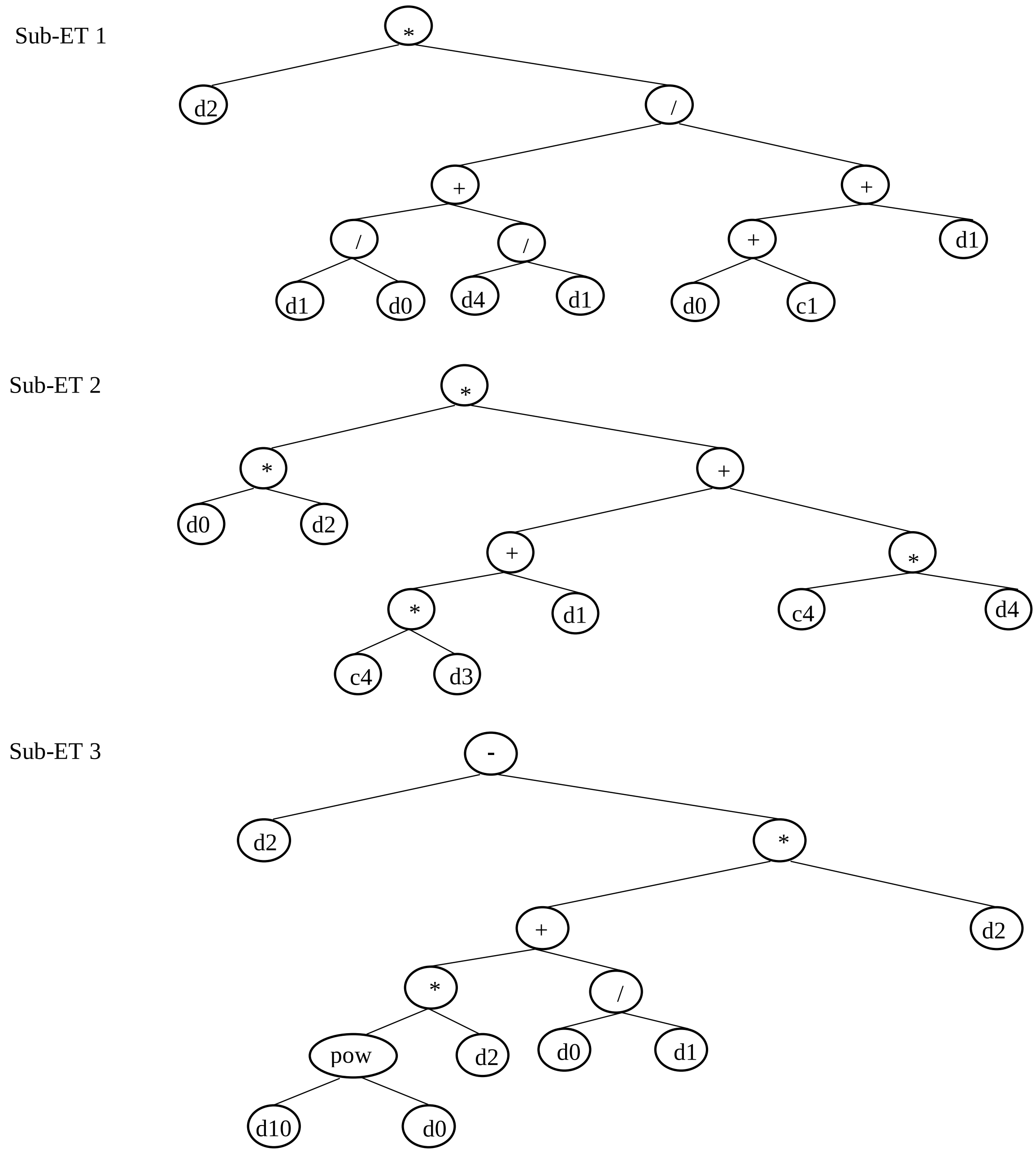

Figure 4 Expression Trees (ET) to formulate GEP for scour depth.

Table 3 Definition of parameters.

Parameters	Definition
d0	V/V_c
d1	y/b
d2	b/B
d3	K_S
d4	$K\theta$
C1 (gene1)	-7.38
C4 (gene2)	2.66

2.5.2 ANN Model

For the ANN prediction models, the same division of the dataset as for GEP, was used. Out of the total 729 data sets, the neural network was trained using 583 data sets (approximately 80%). For testing / validating the network prediction, the remaining 146 data sets 146 (20%) were used. An ANN simulation was performed using Neural Power 2.5. A simple front feed type mesh was trained using the reverse diffusion technique. For further validation and training, the data were normalized before being entered into the program, many trials carried out to get the best ANN structure. ANN comprises three layers with five input neurons as well as five hidden neurons and one output neuron, as shown in Figure 5. For the hidden layers and outputs, the transformation of values across layers was modeled by using the sigmoid activation function. In ANN modelling, the initial weights used are randomly generated for values close to zero. In this study, a neural network with a learning rate of 0.1 and momentum factor of 0.4 was used. For the training model, the maximum number of iterations was 61450, this set for all subsequent models. To assess results, the statistical validation tools determination coefficient (R^2) as well as root mean square error (RMSE) and mean absolute error (MAE) were used.

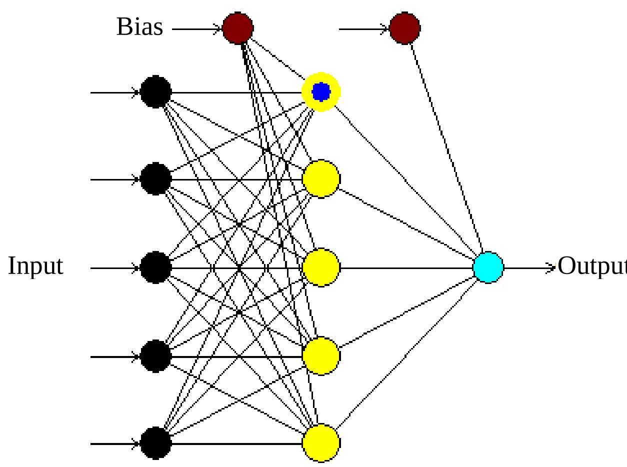

Figure 5 The architecture of the ANN model.

2.5.3 NLR Predicting Model

The same training datasets used to build the GEP and ANN models, were used to build an NLR model. Equation 4 was generated to match the maximum ratio of the depth of scour (ds/b) with the other independent parameters (V/Vc, b/B, y/b, K_S, Kθ).

$$\frac{ds}{\mathrm{b}} = 1.75 * \frac{V}{V_C} + 0.43 * \frac{y}{b} + 0.21 * \frac{b}{B} + 0.16 * K_S - 0.84 * K\theta - 0.87 * \frac{V}{V_C}^2 - 0.28 * \frac{y^2}{b} \tag{4}$$

3. Results and discussion

3.1 Calibration and validation models

The efficacy of Flow-3D modelling was evaluated and validated using data obtained experimentally from [21], the numerical model validated against the experimental model achieving a maximum error ratio between the two of 10%. The predicted scour depth computed by the GEP, ANN and NLR models were plotted against the measured scour depth. The performance of the three different methods was examined by three statistical verification indexes; R^2, RMSE and MAE, as illustrated in Table 4. According to Table 4, the ANN model performed better than the other models, giving high-value predictions: R^2 = 0.93, RMSE=0.129 and MAE=0.088. The GEP model (Equation (3)) predictions (R^2 = 0.89, RMSE=0.152 and MAE= 0.118) were noted to be close to the ANN model while the NLR model (Equation (4)) was not as effective as the others (R^2 =0.79, RMSE=0.221 and MAE=0.176). The training and testing results of scatterplots for the GEP, ANN and NLR models, are presented in Figures 6.

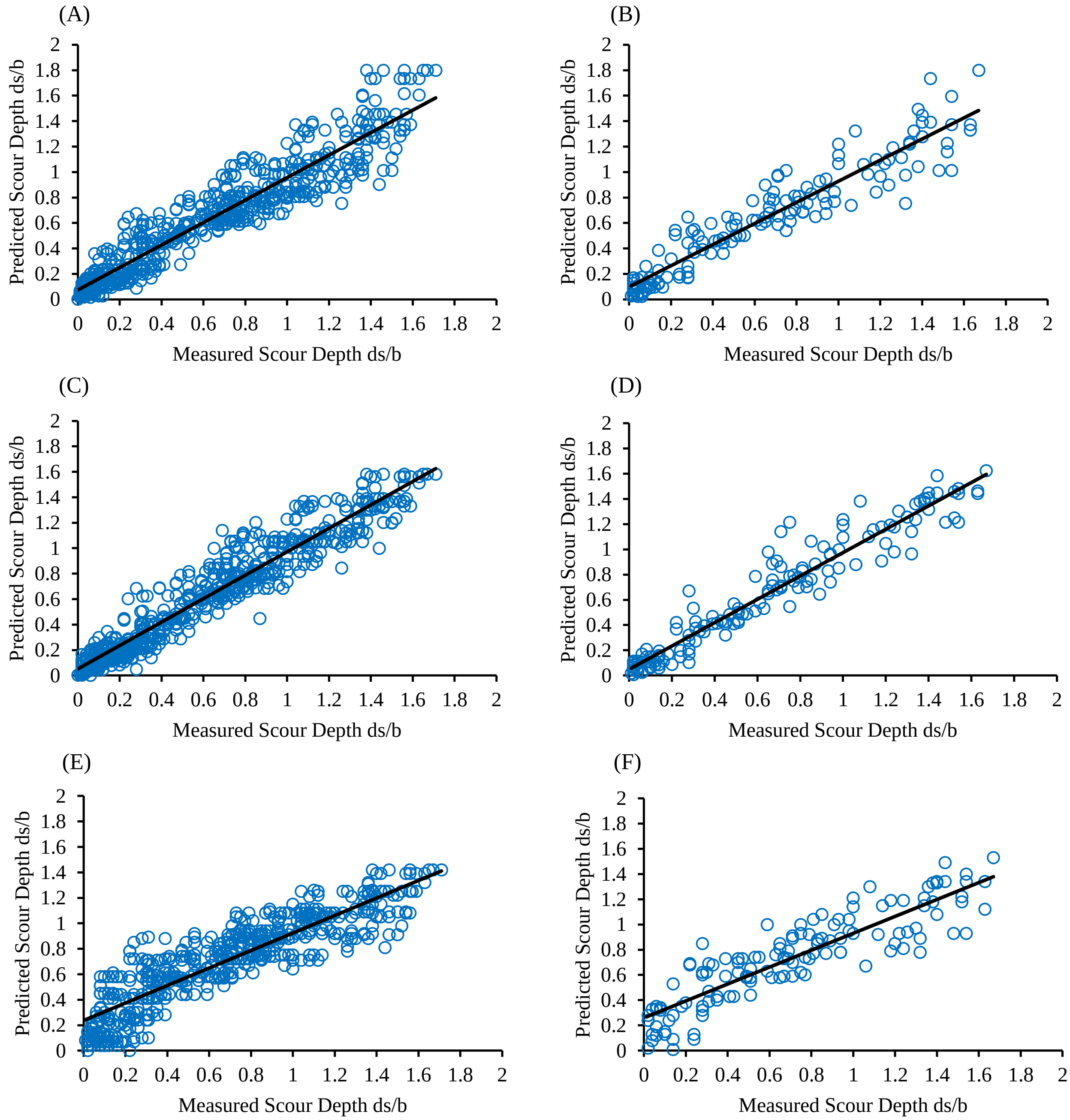

Figure 6 Measured versus predicted scour depth ratios (ds/b) for the GEP model (A-B), the ANN model (C-D**)** and the NLR model (E-F) for training (left) and testing (right).

It is clear from Figure 7 that all three methods are more accurate at predicting local scour on the first half of the x-axis where ds/b is less than one, in comparison to when ds/b is more than one. This could be because when increasing the value of the local scour (ds) with a fixed pier diameter (b), there will be an increase in the velocity of the flow, this leading to the generation of vortices which increase the turbulence of flow [29]. These vortices and turbulence were not included as factors which may have an impact on the prediction of the depth of scour, resulting in a decrease in its predictive accuracy. A unique feature of GEP is that it provides an easy-to-use, explicit empirical expression for its bridge scour model as represented by Equation (3), verified against [21] experimental data, this giving it an advantage over ANN. The maximum scours depth around the circular pier obtained from Equation (3) is 3.2 cm, while the scouring depth obtained from Melville model is 4 cm giving an error rate ratio close to 20%.

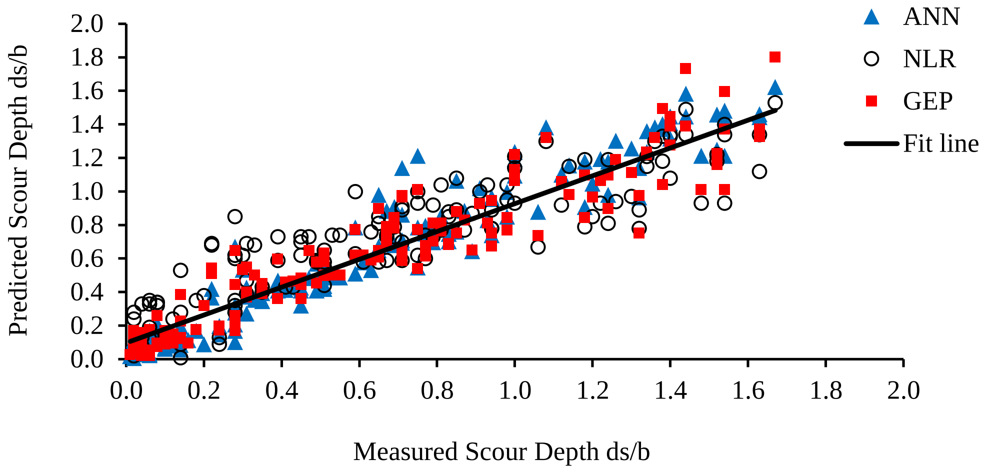

Figure 7 Comparison between GEP, ANN and NLR models (testing data).

In summary, while the NLR equation is not as efficient as GEP and ANN, it still produces reasonably good results. Even though ANN performs better than GEP in terms of scatter plots and statistical measures, it does not provide any overt mathematical expression. GEP has the ability to offer a compressed and explicit arithmetic expression that could be of use to designers in the future. In the context of comparison with previous investigator works, the resulting dataset collected and used in this study covers a broad spectrum and variation of the related model input decision variables in predicting scour depth around the bridge pier. Also, In the current study, the predicted depth of scour by using GEP is more accurate when it comparted with previous literature such as [13,18,30] in terms of statistical indexes.

Table 4 Summary of statistical results for GEP, ANN and NLR.

Models	Training			Testing		
	R^2	RMSE	MAE	R^2	RMSE	MAE
GEP	0.90	0.151	0.115	0.891	0.152	0.118
ANN	0.92	0.128	0.096	0.9302	0.129	0.088
NLR	0.80	0.210	0.167	0.794	0.221	0.176

3.2 Sensitivity analysis

Sensitivity analyses were conducted for the GEP model to define the influence of each input parameter on the predicted depth of scour and to identify the most sensitive parameter(s) which will need detailed and focused attention in future work [30]. There are many operators that influence the predicted depth of scour at bridge piers including pier width ratio, flow depth ratio, mean flow velocity, pier shape and angle of attack. Various input combinations have been examined, as illustrated in Table 5, by eliminating one input parameter in each case, its effect on the expected scour depth in expression of the determination coefficient (R^2) and root mean square error (RMSE) evaluated as the main performance criteria. Figure 8 represents the importance of each input parameter, the importance of these listed from highest to lowest effect on the predicted depth of scour. Figure 8 shows that the influence of the ratio of flow depth (y/b) is about 73% more than the intensity of flow (V/Vc) on the predicted depth of scour by the GEP model. Pier shape (K_S) has the lowest effect on the predicted depth of scour as compared to other input parameters. In summary, depth of flow ratio (y/b) supersedes the other input parameters that have no significant influence on the prediction of the depth of scour, followed by flow intensity (V/Vc), pier width ratio b/B, angle of attack Kθ and pier shape (K_S).

Table 5 Sensitivity analysis for the input parameters regarding the testing data.

GEP models	Model parameters	R^2	RMSE
Model 1	$\frac{d_s}{b} = f\left(K\theta\ ,\frac{y}{b}\ ,K_s\ ,\frac{B}{b}\ ,\frac{V}{V_c}\right)$	0.89	0.152
Model 2	$\frac{d_s}{b} = f\left(K\theta\ ,\frac{y}{b}\ ,K_s\ ,\frac{B}{b}\right)$	0.723	0.257
Model 3	$\frac{d_s}{b} = f\left(K\theta\ ,\frac{y}{b}\ ,K_s\ ,\frac{V}{V_c}\right)$	0.746	0.205
Model 4	$\frac{d_s}{b} = f\left(K\theta\ ,\frac{y}{b}\ ,\frac{B}{b}\ ,\frac{V}{V_c}\right)$	0.878	0.17
Model 5	$\frac{d_s}{b} = f\left(\frac{y}{b}\ ,K_s\ ,\frac{B}{b}\ ,\frac{V}{V_c}\right)$	0.849	0.189
Model 6	$\frac{d_s}{b} = f\left(K\theta\ ,K_s\ ,\frac{B}{b}\ ,\frac{V}{V_c}\right)$	0.327	0.399

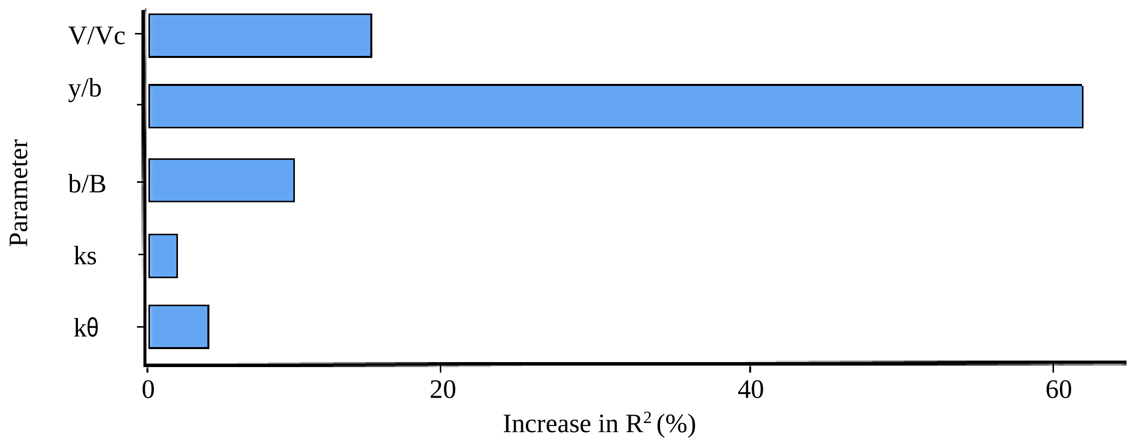

Figure 8 The incremental impact of input variables.

4. Conclusion

The accurate prediction of local scouring around bridge piers is complex and difficult to measure. By applying various modelling techniques, this study aimed to develop a new, more effective empirical equation to predict the depth of local scour around piers of bridges. The parameters most effective at predicting scouring depth were determined by using dimensional analysis. 5 dimensionless parameters were introduced by dimensional analysis; flow intensity (V/V_c), flow depth ratio (y/b), pier width ratio (b/B), shape factor (K_S) and angle of attack ($K\theta$). A functional relationship was created using GEP, its performance compared to ANN and NLR. The GEP model provided smaller values for RMSE (0.152) and MAE (0.118) and a greater R^2 (0.89) value from the values obtained using the conventional NLR model (R^2 =0.79, RMSE=0.221 and MAE=0.176). Regarding statistical measures, GEP's performance for test results is slightly lower than that of ANN as ANN produced a higher value for R^2 (0.93) and lower values for RMSE (0.129) and MAE (0.088). The ANN model is to some extent better than the GEP model, but despite this performance, it is not as advantageous as it does not offer any explicit mathematical expression that is easy to use by bridge engineers. The GEP model produces compact and clear formula, the benefit of this making the GEP model more efficacious and unique when compared with other models studied in this paper. It can therefore be concluded that the GEP model is an effective modeling tool for predicting local scour depth, providing easy and simple to use empirical expressions for modeled response functions. The limitations of GEP equation are: flow intensity (0.55-1), flow depth ratio (0.2-2.95), pier width ratio (0.11-0.15) and for angle of attacks and pier shape factor (0^o-45^o) and (0.71-1.26) respectively. Finally, it is recommended to develop a new experimental formulation which includes the effects of sediment volume, chimney slope, and uniform and irregular sediments on scour depth.

5. References

[1] Shepherd R, Frost JD. Failures in civil engineering: structural, foundation and geoenvironmental case studies. New York: ASCE Publishing; 1995.

[2] Muzzammil M, Gangadharaiah T, Gupta AK. An experimental investigation of a horseshoe vortex induced by a bridge pier. Water Manag. 2004;157(2):109-119.

[3] Jalal HK, Hassan WH. Effect of bridge pier shape on depth of scour. In: Nile K. Basim, editor. 3rd International Conference on Engineering Sciences; 2019 Nov 4-6; Kerbala, Iraq. Bristol: IOP Publishing; 2020. p. 1-16.

[4] Melville BW. Pier and abutment scour: integrated approach. J Hydraul Eng. 1997;123(2):125-136.

[5] Ansari SA, Kothyari UC, Raju KV. Influence of cohesion on scour around bridge piers. J Hydraul Res. 2002;40(6):717-729.

[6] Huang W, Yang Q, Xiao H. CFD modeling of scale effects on turbulence flow and scour around bridge piers. Comput Fluids. 2009;38(5):1050-1058.

[7] Hassan WH, Jassem MH, Mohammed SS. A GA-HP model for the optimal design of sewer networks. Water Resour Manag. 2018;32(3):865-879.

[8] Azamathulla HM, Ghani AA, Zakaria NA, Guven A. Genetic programming to predict bridge pier scour. J Hydraul Eng. 2010;136(3):165-169.

[9] Mohamed TA, Noor MJ, Ghazali AH, Huat BB. Validation of some bridge pier scour formulae using field and laboratory data. Am J Environ Sci. 2005;1(2):119-125.

[10] Arneson LA, Zevenbergen LW, Lagasse PF, Clopper PE. Evaluating scour at bridges 5th ed. Final report. Virginia; National Highway Institute (US); 2012 Apr. Report No.: FHWA-HIF-12-003 HEC-18.

[11] Jain SC, Fischer EE. Scour around circular bridge piers at high Froude numbers. Final report. Iowa: Department of Transportation, Federal Highway Administration, Office of Research, Environmental Division;1976 Apr. Report No.:FHWA-RD-79-104.

[12] Melville BW, Sutherland AJ. Design method for local scour at bridge piers. J Hydraul Eng. 1988;114(10):1210-1226.

[13] Muzzammil M, Alama J, Danish M. Scour prediction at bridge piers in cohesive bed using gene expression programming. Aquat Procedia. 2015;4:789-796.

[14] Hassan WH. Application of a genetic algorithm for the optimization of a location and inclination angle of a cut-off wall for anisotropic foundations under hydraulic structures. Geotech Geol Eng. 2019;37(2):883-895.

[15] Baghban A, Jalali A, Shafiee M, Ahmadi MH, Chau KW. Developing an ANFIS-based swarm concept model for estimating the relative viscosity of nanofluids. Eng Appl Comput Fluid Mech. 2019;13(1):26-39.

[16] Govindaraju RS. Artificial neural networks in hydrology. I: preliminary concepts. J Hydrol Eng. 2000;5(2):115-123.

[17] Azmathullah HM, Deo MC, Deolalikar PB. Neural networks for estimation of scour downstream of a ski-jump bucket. J Hydraul Eng. 2005;131(10):898-908.

[18] Khan M, Azamathulla HM, Tufail M. Gene-expression programming to predict pier scour depth using laboratory data. J Hydroinformatics. 2012;14(3):628-645.

[19] Jalal HK. Numerical study of optimum pier shape for safe bridge. [Thessis]. Karbala:University of Kerbala; 2019.

[20] Bobrowsky PT, Marker B, editors. Encyclopedia of engineering geology. Cham: Springer Nature Switzerland AG; 2018.

[21] Melville BW. Local scour at bridge sites [PhD Thesis] Auckland: University of Auckland; 1994.

[22] Ferreira C. Gene expression programming: a new adaptive algorithm for solving problems. Complex Syst. 2001;13(2):87-129.

[23] Koza JR. Genetic programming: on the programming of computers by means of natural selection. 1st ed. Massachusetts: MIT press; 1992.

[24] Ferreira C. Automatically defined functions in gene expression programming. In: Ajith A, Nedjah N, Mourelle LM, editors. Genetic systems programming: theory and experiences. 1st ed. Berlin: Springer; 2006. p. 21-56.

[25] Hassan WH. Application of a genetic algorithm for the optimization of a cutoff wall under hydraulic structures. J Appl Water Eng Res. 20172;5(1):22-30.

[26] Onen F. Prediction of scour at a side-weir with GEP, ANN and regression models. Arab J Sci Eng. 2014 ;39(8):6031-6041.

[27] Hassan WH. Climate change impact on groundwater recharge of Umm er Radhuma unconfined aquifer Western desert, Iraq. IJHST. 2020;10(4):392-412.
[28] Azamathulla HM, Ghani AA, Leow CS, Chang CK, Zakaria NA. Gene-expression programming for the development of a stage-discharge curve of the Pahang river. Water Resour Manag. 2011;25(11):2901-2916.
[29] Fattah MY, Hassan WH, Rasheed SE. Effect of geocell reinforcement above buried pipes on surface settlement. Int Rev Civ Eng. 2018;9(2):86-90.
[30] Fattah MY, Hassan WH, Rasheed SE. Behavior of flexible buried pipes under geocell reinforced subbase subjected to repeated loading. Int J Geotech Earthq Eng. 2018;9(1):22-41.