Ain Shams Engineering Journal (2013) 4, 717–722

Ain Shams University
Ain Shams Engineering Journal
www.elsevier.com/locate/asej
www.sciencedirect.com

CIVIL ENGINEERING

Modeling of local scour depth downstream hydraulic structures in trapezoidal channel using GEP and ANNs

Yasser Abdallah Mohamed Moussa *

Water Engineering Department, Faculty of Engineering, Zagazig University, Egypt

Received 19 November 2012; revised 21 February 2013; accepted 16 April 2013
Available online 5 June 2013

KEYWORDS
Local scour;
GEP;
ANN;
Current deflector;
Trapezoidal channel

Abstract Local scour downstream stilling basins is so complex that it makes it difficult to establish a general empirical model to provide accurate estimation for scour depth. Lack estimation of local scour can endanger to stability of hydraulic structure and can cause risk of failure. This paper presents Gene expression program (GEP) and artificial neural network (ANNs), to simulate local scour depth downstream hydraulic structures. The experimental data is collected from the literature for the scour depth downstream the stilling basin through a trapezoidal channel. Using GEP approach gives satisfactory results compared with artificial neural network (ANN) and multiple linear regression (MLR) modeling in predicting the scour depth downstream of hydraulic structures.

1. Introduction

Scour is a natural phenomenon caused due to the erosive action of flowing stream on alluvial beds which removes the sediment around or near structures located in flowing water. In addition, when a hydraulic structure such as dam, regulator, spillway, or bridge, is placed in a hydraulic/marine environment, the presence of the structure will change the flow pattern in its immediate neighborhood, resulting in these changes usually cause an increase in the local sediment transport capacity and thus lead to scour. Scour can induce failure of hydraulic and marine structures [1]. So, local scour modeling is an important issue in environmental/water resources engineering in order to prevent degradation of river bed and safe the stability of grade control structures [2,3]. The river bed in the vicinity of a hydraulic structure is generally protected against current, waves, and eddies [4–6,1,7]. The effect of baffles on scour depth over stilling basis was investigated by many researchers [8–16]. ANN was used to investigate its possibility as a modeling tool for simulation of tidal flow in two-dimensional flow field [17]. An ANN has been employed to predict scour at a culvert outlet [18,19]. The scour depth downstream hydraulic structures were predicted using artificial neural network [20]. In addition, it was employed to predict flow characteristics in irregular open channel [21] and sediment load [22].

* Tel.: +20 01111890996.
E-mail addresses: Yasser_eng1997@yahoo.com, Yasser_eng1997@zu.edu.eg.

Peer review under responsibility of Ain Shams University.

ELSEVIER Production and hosting by Elsevier

2090-4479 © 2013 Ain Shams University. Production and hosting by Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.asej.2013.04.005

Moreover, the local scour depth downstream spillway and ski-jump, was predicted [23,24], respectively. Gene expression programming, GEP, is used by many researchers, to develop combined run off [25], prediction of surface roughness [26], investigate the hydraulic jump characteristics [27]. In addition, this technique is used as a new algorithm for solving problems [28]. GEP is used to predict the local scour depth for different types of hydraulic structures [29–33]. This paper presents the modeling of local scour depth though the trapezoidal channel using artificial techniques; ANNs and GEP. The stilling basin is provided with current deflector at different positions from the sluice gate, to control and minimize the local scour depth downstream hydraulic structure.

2. Overviews of ANNs and GEP

2.1. The artificial neural networks

ANNs as a technique of prediction could be used to predict the local scour depth by building a multilayer feed forward network. Such type of ANN consists of several layers (Fig. 1); each has one or more units (neurons). Each unit of the first layer (input layer) receives the input data of an independent factor (variable), multiplies each input by the connection weight, and transmits the result to the corresponding unit in the hidden layer where the activation function is applied. The results from the hidden layer are transferred to the output layer by multiplying the output of each neuron in the hidden layer by the corresponding connection weight between hidden and output neurons. The output layer produces the network output for further processing of the data. At this stage, the network output is compared to the desired (target) output to compute the error. If the error is acceptable, then the output is assumed to be correct otherwise the weights of the connection are adjusted starting from the output layer and propagating backward. Once the weights are updates, a new iteration begins and so on until training is completed. The training is stopped when the error level is reached or when the number of iterations is finished. The basics of the ANNs were introduced by many authors, e.g. [34,17,35].

2.2. Gene expression programming

GEP is considered as an extension of Genetic programming (GP). Gene expression programming is a full-fledged genotype/phenotype system, with the genotype totally separated from the phenotype, where in GP, genotype and phenotype are mixed together in a simple replicator system. GEP computer program is encoded in linear chromosomes composed of genes structurally organized in a head and a tail. The chromosomes function as a genome and are subjected to modification by means of mutation, transposition, root transposition, gene transposition, gene recombination, and one- and two-point recombination. The chromosomes encode expression trees which are object of selection. The creation of these separates entities (genome and expression tree) with distinct functions allows the algorithm to perform with the high efficiency that greatly surpasses existing adaptive techniques [28]. The interplay of chromosomes and expression trees in GEP implies an unequivocal translation system for translating the language of chromosomes into the language of expression trees (ETs). The genetic code of Gene expression programming is very simple: a one-to-one relationship between the symbols of chromosome and the nodes they represent in the trees. The rules are also very simple. They determine the spatial organization of nodes in the expression trees and the type of interaction between sub-ETs. Therefore, there are two languages in GEP, the language of genes and the language of expression trees. This unequivocal bilingual notation is called karva language. Expression trees and Karva Language are explained in details by [36,28]. The steps for GEP are shown in Fig. 2. The process begins with random generation of chromosome of the initial population. Then, the chromosomes are expressed, and fitness of each individual is evaluated. The individuals are then selected according to fitness to

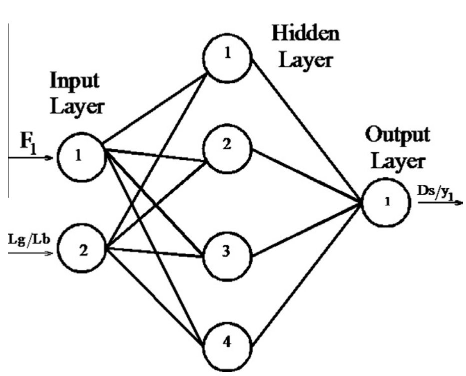

Figure 1 Structure shape of ANN.

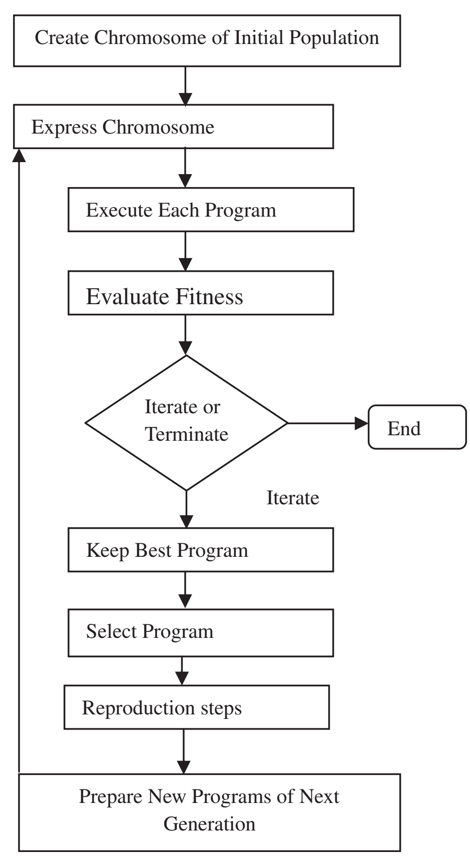

Figure 2 Flow chart of a gene expression algorithm, Ferreira 2001.

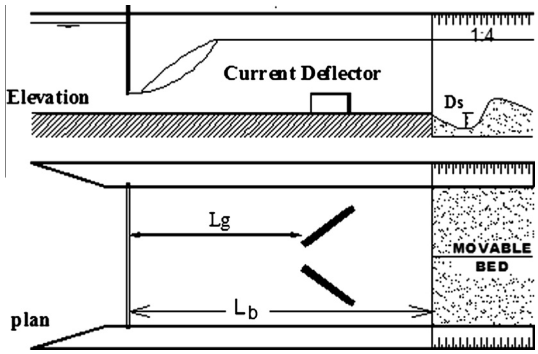

Figure 3 Definition sketch for the experimental model Shaheen [37].

Table 1 Ranges of data employed to train and test the GEP, ANN, and MLR.

Parameter	Range
Froude number F_1	1.45–8.45
Grain size	1.77 mm
Channel side slope	1 (Horizontal): 4 (Vertical)
Current deflector configurations	Lg/L_b = 0.00–0.74, Height = 2.5 cm, With angle = 10.2°

Table 2 Parameters of the GEP models.

Function set	+, −, ×, /, *S*qrt, Exp, Ln, Sin, Cos, Atan	Mutation rate	0.044
Number of gene	23	IS transportation rate	0.1
Head size	7	RIS transportation rate	0.1
Linking function	+	Gene transportation rate	0.1
Number of generation	1000	One-point recombination rate	0.3
Number of population	100	Two-point recombination rate	0.3
Number of best individuals cloning	10	Gene recombination rate	0.1

reproduce with modification, leaving progeny with new traits. The individuals of this new generation are, in their turn, subjected to the same developmental process: expression of the genomes, confrontation of the selection environment, and reproduction with modification. The process is repeated for a certain number of generations or the required accuracy is achieved [28]. In GEP system, the operators used for the genetic modification of chromosomes are explained [36].

3. Theoretical background

Fig. 3 shows a definition sketch of the experimental model [37]. Using the principles of the dimensional analysis, the following relationship is obtained;

$$D_s/y_1 = f(Lg/L_b, F_1) \tag{1}$$

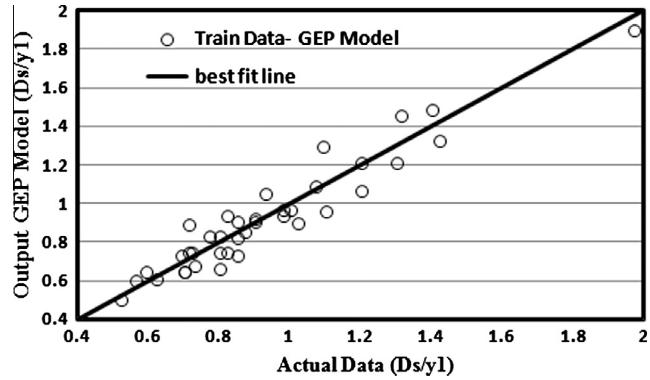

Figure 4 Experimental data versus the output of GEP model for train data set.

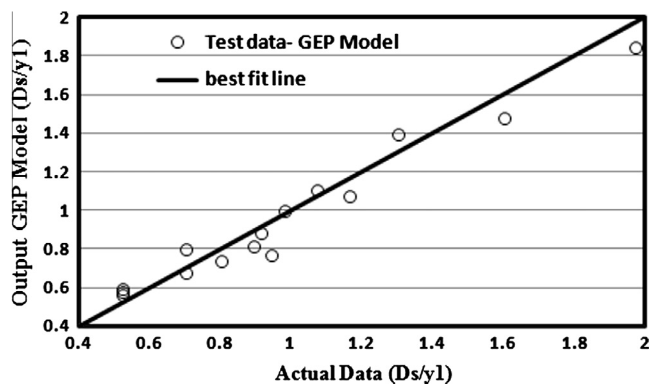

Figure 5 Experimental data versus the output of GEP model for test data set.

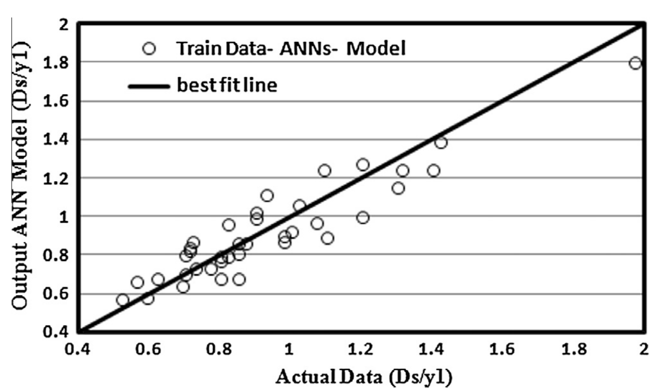

Figure 6 Experimental data versus the output of ANN model for train data set.

In which, D_s is the local scour depth downstream stilling basin, y_1 is the super critical flow depth, Lg is the length from gate to the beginning of Current deflector, L_b is the basin length, and F_1 is the initial Froude number at the depth of y_1. The experimental data are collected from [37]. The ranges of various parameters included in the present study are summarized in Table 1.

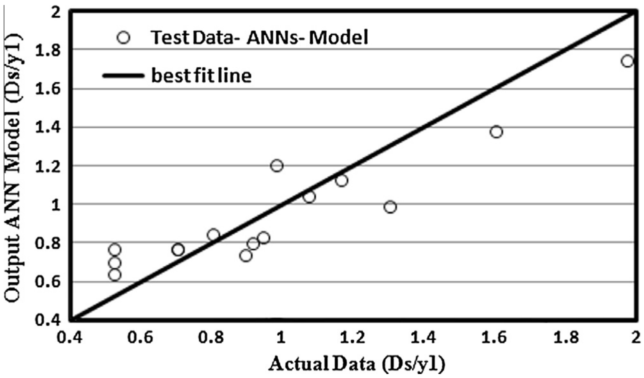

Figure 7 Experimental data versus the output of ANN model for test data set.

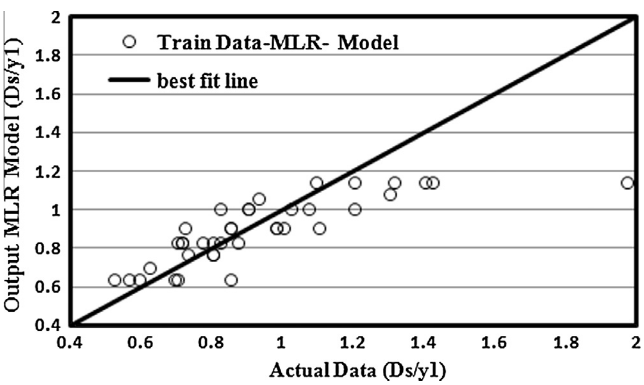

Figure 8 Experimental data versus the output of MLR model for train data set.

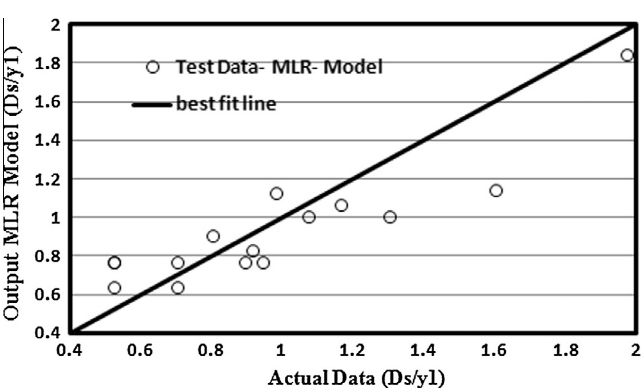

Figure 9 Experimental data versus the output of MLR model for test data set.

4. Modeling of local scour depth using ANNs, GEP and MLR

4.1. ANNs model

The experimental data are divided into 70% of the data for the training of the network and the remaining 30% of the data for testing the network prediction. The Neural Connection Software 1998 is used to train the network [38]. All the data are normalized using the zero-mean-unit-standard deviation. Several trials are conducted to have the best structure of the artificial neural network. The best values of the initial weights (± 0.01), the transfer functions (Sigmoid), the number of hidden neurons and the best number of iterations are 4, and 2000 respectively, See Fig. 1.

4.2. GEP model

Automatic Problem Solver ® – APS 3.0 – (www.gepsoft.com), GEP a powerful soft computing software package, is used in modeling the local scour depth downstream stilling basin through a trapezoidal channel. The previous 70% of data set is used to build GEP model and the rest of observations for check the test data set. The parameters used in the GEP models are given in Table 2. Froude number (F_1), and relative position of current deflector Lg/L_b are assigned to the columns as independent input variables while relative local scour depth D_s/y_1 is used as dependent output variable. Therefore, a D_s/y_1 model of output variable is developed by using GEP.

4.3. MLR model

The same training data sets for building GEP and ANN models are used also to build the multiple regression model. The following equation is obtained to correlate the relative scour depth with the other independent parameters (Froude number and relative position of current deflector).

$$D_1/y_1 = -0.57 + 1.6e(-5)F_1 - 3.2e(-3)(L_g/L_b) + 1.13e(-3)(L_g/L_b)^{0.2} \quad (2)$$

5. Discussion of results

Numerical results using GEP, ANNs, and multiple linear regressions (MLR) techniques are plotted versus the experimental results; Figs. 4 and 5 show the experimental data versus numerical results using GEP for both train and test data sets, respectively. The same plots are prepared for ANNs techniques (Figs. 6 and 7) and MLR (Figs. 8 and 9). The statistical

Table 3 Results of GEP, ANN, and MLR Models.

Model	Data set	R^2	Stander error	AMRE $= ABS\left(\frac{D_s(Measured)-D_s(modeloutput)}{D_S(Measured)}\right)$ (Absolute mean relative error)
GEP	Train data	0.86	0.11	0.08
	Test data	0.96	0.08	0.07
ANN	Train data	0.71	0.25	0.12
	Test data	0.74	0.20	0.13
MLR (Eq. (2))	Train Data	0.64	0.50	0.14
	Test data	0.67	0.25	0.20

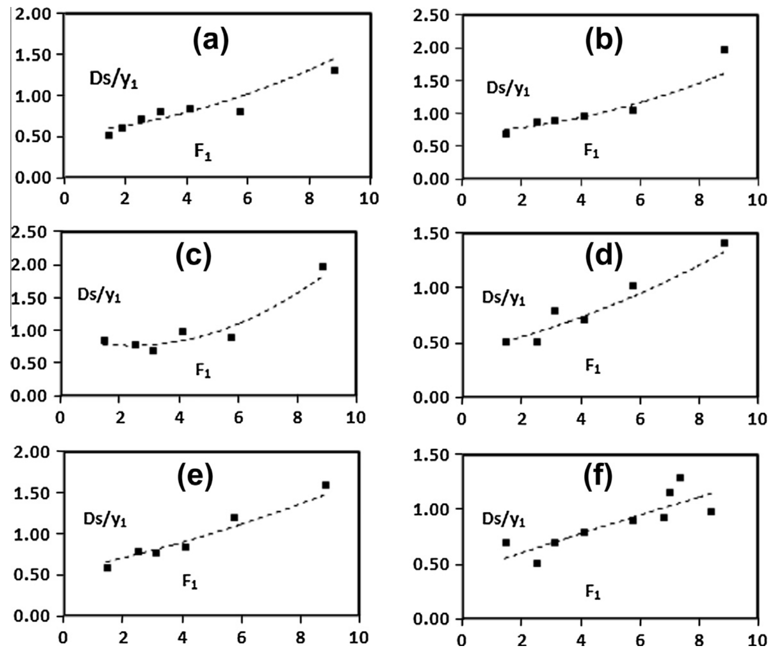

Figure 10 Relationship between F_1 and D_s/y_1 for GEP simulated model and experimental data for different relative current deflector positions (Lg/L_b = (a) 0.0, (b) 0.01, (C) 0.06, (d) 0.11, (e) 0.36, and (f) 0.76).

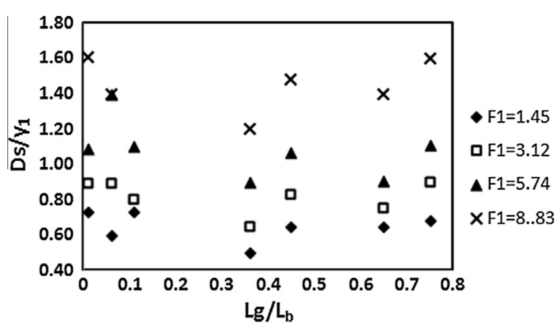

Figure 11 Relationship between Lg/L_b and D_s/y_1 for GEP predicted data and different Froude numbers.

results of model predictions for training and testing sets are given in Table 3. It is clear that GEP model predicted the scour depth for both training and testing set with lower error AMRE (0.08 and 0.07) and higher accuracy R^2 (0.86 and 0.96), respectively. Table 3 shows that the outperforming of the GEP model is considered the best one compared to ANNs and MLR models.

The numerical results for GEP model are presented versus the experimental data for different relative positions of current deflector (Lg/L_b = 0:0.76), Fig. 10. This figure shows that GEP expresses well the experimental data for different relative position of current deflector. The best location of the current deflector to have minimum local scour depth equals (Lg/L_b), 0.37, Fig. 11.

6. Conclusions

A mathematical model between is generated by Gene expression programming (GEP) for the purpose of predicting local scour depth downstream stilling basin through trapezoidal channel. The stilling basin is provided with current deflector placed at different relative positions to control the local scour depth. In addition, an artificial neural network (ANN) and multiple linear regression (MLR) models are implemented to predict the scour depth downstream the hydraulic structures. From this study, it is clearly found that the Gene expression programming model simulate the local scour depth downstream stilling basin effectively compared to the other models (ANN, MLR). GEP model is showing well the effect of current deflector on the scour formed through the trapezoidal channel section.

Acknowledgement

The Author would like to express his appreciation to Engineering Marowa Shaheen, Ministry of Water Resources and Irrigation, for providing the experimental data used in this paper.

References

[1] Azamathulla HM. Neural networks to estimate scour downstream of ski-jump bucket spillway. PhD Thesis, Indian Institute of Technology, Bomba, India; 2006.
[2] Laucelli D, Giustolisi O. Scour depth modelling by a multi-objective evolutionary paradigm. Environ Modell Softw 2011;26(4):498–509.
[3] Abdellateef M, Abdelhafiz EA, Khalifa A. A study of scour downstream one vent regulator. In: Albertson, Kia, editors. Design of hydraulic structures. Rotterdam: Balkema; 1989.
[4] Mason PJ, Arumugam K. Free jet scours below dams and flip buckets. J Hydraul Eng ASCE 1985;111(2):220–35.
[5] Shields FD, Knight JR, Cooper SS. Incised stream physical habitat restoration with stone weirs. Regul Rivers: Res Manage 1995;10:181–98.
[6] Hoffmans GJ, Verheij HJ. Scour manual. Rotterdam: Balkema; 1997. p. 68–87.

[7] Guven A, Gunal M. Prediction of scour downstream of grade-control structures using neural networks. J Hydraul Eng 2008;134(11):1656–60.
[8] Osman C, Korkt O, Rifat T. A study of scours at the end of stilling basin and use of horizontal beams as energy dissipation. Int Comm High Barrages Madrid 1973:23–37.
[9] Nettleton Peter C, McCorquodal JA. Radial stilling basin with baffles. Proc Can Soc Civil Eng Montreal Canada 1983;2:561–70.
[10] Nashta A. The proper location of floor sill with scour reach downstream of heading-up structure. Bull Fac Eng, Assuite Univ 1995;23(2):11–9.
[11] Mohamed MS, Negm AM, EL-Saiad AA. Combined effects of baffle piers and end sill on scour downstream of hydraulic structure. Civil Eng Res Mag, Fac Eng, Al-Azhar Univ, Egypt 2000;4:1620–38.
[12] Negm AM, Mohamed MS, El-saiad AA. Combined effects of baffle piers and an end sill on scour downstream of hydraulic structures. Civil Eng Res Mag (CERM), Al-Azhar Univ, Egypt 2000;22(4):1620–38.
[13] Negm AM, Abdel-Aal GM, Elfiky M, Mohamed YA. Optimal position of curved deflector to minimize scour downstream multi-vents regulators. In: 12th International water technology conference, ITWTC12, Alexandria, Egypt; 2008.
[14] EL Masry AA, Sarhan TE. Minimization of scour downstream heading up structures using single lines of angle baffles. Eng Res J, Helwan Univ, Fac Eng, Mataria, Cairo, Egypt 2000;69:192–207.
[15] EL Masry A. Minimization of scour downstream heading up structures using double lines of angle baffles. In: Sixth international water technology conference, IWTC, Alexandria, Egypt; 2001.
[16] El-Gamal MM. Effect of using three-lines of angle baffles on scour downstream heading-up structures. Mansora Eng J, Fac Eng, Mansora Univ, Egypt 2001;26(2):73–485.
[17] Dibike YB, Minns AW, Abbott MB. Applications of artificial neural networks to the generation of wave equations from hydraulic data. J Hydraul Res 1999;37(1):81–97.
[18] Liriano SL, Day RA. Prediction of scour depth at culvert outlets using neural networks. J Hydro-Informatics 2001;3(4):231–8.
[19] Azamathulla HM, Haque AM. Knowledge extraction from trained neural network scour model at culvert outlets. Neural Comput Appl 2012(September). http://dx.doi.org/10.1007/s00521-012-1164-2.
[20] Mohamed S. Artificial neural net work prediction of maximum scour hole downstream hydraulic structures. In: 11th International water technology conference IWTCII, Sharm EL Sheikh, Egypt; 2007.
[21] Abdeen M. Neural network model for predicting flow characteristics in irregular open channel. Sci J, Fac Eng-Alexandria Univ, Alexandria 2001;40(4):539–46.
[22] Nagy HM, Watanabe K, Hirano M. Prediction of sediment load concentration in rivers using artificial neural network model. J Hydraul Eng 2002;128(6):588–95.
[23] Azamathulla H, Abghani A, Zakaria NA. An ANFIS based approach for predicting the scour below Flip-Bucket spillway. Riverside Kuching, Sarawak, 6–8 Malaysia; 2008.
[24] Azmathullah HM, Deo MC, Deolalikar PB. Neural networks for estimation of scour downstream of ski-jump bucket. J Hydraul Eng 2005;131(10):898–908.
[25] Fernando DK, Shamseldin AY, Abrahart RJ. Using gene expression programming to develop a combined runoff estimate model from conventional rainfall-runoff model outputs. In: 18th world ImaCS/MODSIM congress, Caims, Australia 13–17; 2009.
[26] Yang Y, Xinyu Li, Ping Jiang, Liping Zhang. Prediction of surface roughness in end milling with gene expression programming. In: Proceedings of the 41st international conference on computers & industrial engineering; 2010.
[27] Eldrandaly K, Negm AM. Performance evaluation of gene expression programming for hydraulic data mining. Int Arab J Inform Technol 2008;5(2).
[28] Ferreria C. Gene expression programming: a new adaptive algorithm for solving problems. Complex Syst 2001;13(2):87–129.
[29] Mujahid Khan H, Azamathulla HM, Tufail. Gene-expression programming to predict pier scour depth using laboratory data. J Hydroinformatics 2012;14(3).
[30] Azamathulla HM. Gene expression programming for prediction of scour depth downstream of sills. J Hydrol 2012:169–72, 460–461C.
[31] Azamathulla HM. Gene-expression programming to predict scour at a bridge abutment. IWA J Hydroinformatics 2012;14(2):324–31.
[32] Azamathulla HM, Haque AA. Prediction of scour depth at culvert outlets using gene-expression programming. Int J Innovative Comput Inform Control (IJICIC) 2012;8(7):5045–54.
[33] Mohammadpour R, Ghanib A, Azamathullac HM. Estimation of dimension and time variation of local scour at short abutment. Int J River Basin Manage 2013.
[34] Dibike YB, Abbott MB. Application of artificial neural networks to the simulation of a two dimensional flow. J Hydraul Res 1999;37(4):435–46.
[35] Negm AM. Prediction of hydraulic design parameters of expanding stilling basins using artificial neural networks. Egypt J Eng Sci Technol, EJEST 2002;6(1):1–24.
[36] Ferreira C. Gene-expression programming: mathematical modeling by an artificial intelligence. Berlin, Germany: Springer; 2006.
[37] Shaheen M. Scour DS gates in non-rectangular channels. Thesis MsC. Zagazig university, Egypt; 2009.
[38] Neural Connection. Software and manuals. SPSS/Recognition Systems Limited; 1998.

Mr. **Yasser A.M. Moussa** received the M.Sc. and Ph.D degrees in civil engineering department from college of engineering, Zagazig University, Egypt in 2002 and 2005 respectively. During 2009, Dr Yasser Moussa was a Post Doctorate fellow with Hydroscience and Engineering, college of Engineering, University of Iowa, USA. Currently, he is an associate professor at college of engineering, Zagazig University, Egypt. His research interests are open channel hydraulics, stilling basins, sediment transport, simulation models, and artificial intelligence.