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A Study of Accuracy and Application of Genetic Programming for estimation of Scour Depth around Bridge Piers, below pipelines and Downstream of Bucket Overflow

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ABSTRACT

Scour is a significant issue in the safety of hydraulic structures such as the dam's downstream of bucket overflow, lower valve downstream, bridge piers and below pipelines. Many laboratories have studied the effect of different variables on the scour depth of these structures. Various models like neural networks (ANN), categorizing data (GMDH) and regression equations predicted the scour depth in sensitive hydraulic structures. In this study, the accuracy and application of genetic programming (GP) in the downstream of the dam's overflow, bridge piers and below pipelines is examined. From these examinations the achieved result was that the GP model, when utilized to estimate the downstream scour depth of bucket overflow, has a higher coefficient of determination ($= 0.977R^2$) than when applied to the bridge piers and below pipelines. When this model is used for the estimation of the scour depth below pipelines, it has a lower absolute error ($\delta=9.9$) than the other two cases. The root-mean-square error (RMSE) of GP model for prediction of the scour depth below pipelines is less than the other cases. In the bridge piers, GP model has the least root-mean-square error. When the GMDH model is taught with genetic programming, the outcome will have a higher coefficient of determination.

Key Words: Scouring, GP Model, Bridge Piers, Overflow, Pipelines

INTRODUCTION

The bed erosion at the banks of rivers, streams, downstream of bucket overflow and downstream of the lower valve due to the flow is called scour. The difference between the eroded bed and the initial bed is called scour depth. One of the important issues in water and hydraulic is the estimation of scour depth. Primarily, knowing this phenomenon and, secondly, the appropriate estimation and assessment of the scour level are necessary and vital to consider in bridge designing [1]. In this study, the scouring of bridge piers, pipelines and downstream of bucket overflow was examined, using genetic programming (GP) model. Afterwards, a definition of scouring of the three mentioned structures and the overall structure of GP model is expressed.

Pipeline Scour:

Scour is a significant issue for the rupture of submarine pipelines. The interaction between pipelines and the bed prone to erosion under the flow and or wave conditions may cause scouring around the pipelines. If the free pipe gap is big enough, resonance phenomenon including oscillatory process may occur in the flow below pipes to solve and structure the final rupture. The accuracy for the estimation of the scour depth is very essential in designing submarine pipelines [2].

Some of the old equations which were developed in the past to balance the scour depth below pipelines include Chao and Hennessy [3], Kjeldsen [4], Ibrahim [5], and Chiew [2]. While the main objection to these formulas is that the old formulas have not modeled the scour process accurately, half of the old methods are synthetic experimental and field observations with physical quantity and regression ratios are often used for predicting scour. Yet, regression process can have many uncertainties; the main drawback is adaptive dependent of the complex process of approximate scouring and the extensive average terms of the original sample. Consequently, calculating scour depth will be far different than the actual amount.

Recently, forecasting methods such as artificial networks (ANN) [6], and inductive system (ANFIS) [7], were used for the effective estimation of scour depth around hydraulic structures [8].

Analyzing Local Scour of Submarine Pipelines in the GP Model

The variables effective on the balance of scour depth (d_s) below pipeline in the persistent flow are shown on a spherical, uniform bed and non-adhesive sediments in figure 1 [8], which are the flow conditions, sediment features and pipe geometry. The scour depth can be dependent on a general function. [9]

(1)

$$d_s = f(\rho, \rho_s, \nu, Q, Y, g, d_{50}, S_f, D)$$

In which ρ = fluid density, ρ_s = buoyant density sedimentation, ν = fluid kinematic viscosity, Q = discharge, Y = flow depth, g = constant acceleration of gravity, d_{50} = average diameter of particles, S_f = slope of energy line, D = pipeline diameter, d_s = scour depth balance. The nine variables in equation 1 can be reduced to six parameters without dimension. π is applied rule for equation 1 with the variables fundamental p, ρ and Q . and after dimension leads to equation 2.

(2)

$$\frac{d_s}{D} = \varphi\left(\tau_*, \frac{Y}{D}, \frac{D}{d_{50}}, R, S_f, F\right)$$

In which τ_* = cover parameter without dimension related to transferring sediments, $\frac{D}{d_{50}}$ = soil feature without dimension, R = Reynolds number, S_f = slope of energy line, F = Froude number.

The effect of Reynolds number under a turbulent flow on a coarse bed is considered insignificant.

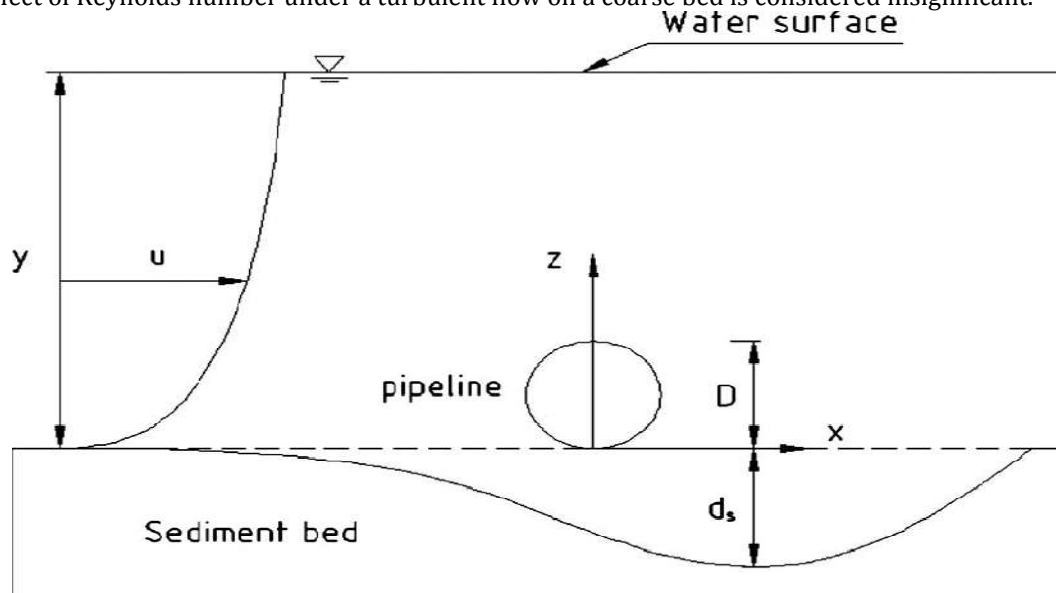


Figure (1): Local scour below pipelines

Genetic programming (GP) and ANN have been widely utilized in some branches of soft computing in hydraulic engineering. In larger fields, several researchers ([6], [7], [8]) have examined the scour around and downstream of hydraulic structures using ANN. Recently, gene programming (GEP), which is an adjoint of GP, has been the interest of researchers in predicting features of hydraulic structures.

Scouring of Bridge Piers:

The existence of a bridge pier in canal may cause a sudden change in the flow pattern which may result in the scour of the bridge pier. The rupture of black bridge pier in New Zealand is the result of the scour of piers in the river bed [10]. The flow mechanism around the pier structure is complicated; therefore, establishing a general scientific model for the prediction of scour depth (d_s) is difficult. A reliable prediction of d_s is the biggest important factor in safety, economy and according to the technical principles and design of bridge piers. Often, the formulas of prediction d_s are available in writings, which have expanded using regression methods commonly acceptable. Johnson [11] reported that the formula offered by Melville and Sutherland provides a greater prediction than any other formulae. Recently, Mohamed [12] demonstrated that the formula of Laursen and Toch [13], and Colorado University (CSC) has provided an acceptable prediction while the above-mentioned formula offered by Melville and Sutherland [14], Jain and Fischer [15] is pier scour prediction based on comparison of some bridge pier scour formulae using laboratory and field data. Appropriate methods such as artificial neural network (ANN) and neuro-fuzzy

adaptive system [16] recently revealed an effective product of d_s prediction. ANN provided a report of good and reasonable solution for the problems of hydraulic engineering in non-linear cases and balanced relationship between input and output pairs according to data [6], [7].

A definition of some prediction models of bridge pier scour depth

Several models and methods for the prediction of bridge pier scour depth have been utilized. In this part, one such model has been pointed out:

Group Method of Data Handling (GMDH):

GMDH network is a learning machine based on general rule of the organizer’s argument itself, which was suggested by Ivakhnenko in the year 1960. Moreover, those series of functions like planting, training, grafting and selection and rejection of particles, are the debate to determine input variables, model structure and parameters and model selection using general rule of termination.

GMDH network is a very flexible structure which can combine two incompatible pairs and is an effective algorithm like genetic algorithm, group genetic program of optimization particles and recursive diffusion. The record research has revealed that grafting has provided a lot of solutions for engineering problems. This method was utilized for the prediction of bridge pier scour depth in various ways, which has been demonstrated in table 1.

According to table 1, it was specified that group categorizing method of temporal manual data which is trained using genetic programming has a higher coefficient of determination.

Table (1): Examining accuracy of different states utilized in GMDH model

| Model | Testing stage | | |
|--------------------------------|---------------|-------|--------------|
| | R^2 | RMSE | MAE |
| GMDH - GP | 0.96 | 0.177 | 0.138 |
| GMDH -BP | 0.9 | 0.23 | 0.2 |
| GMDH - LMwith angle 45degree | 0.9 | 0.18 | 0.108 |
| GMDH - LM with angle 90 degree | 0.85 | 0.25 | 1.3 |

Artificial neural network method in view model for estimation of bridge pier scour depth:

Artificial neural network is actually a model of human brain. This network is a mathematical structure which has the ability to demonstrate processes and nonlinear desired compounds for linking the input and output of each system. The neural network consists of neural cells called neurons. The neurons of artificial neural network are in fact a very simple form of biological neurons. Figure 2 [17]. A typical network ordinarily consists of one input layer, a middle (hidden) layer and an output layer. The input layer is a transferring layer and a means to provide data. The last layer or the output layer has been formed by the amounts predicted by the network and thus introduces model output. And the middle layer which is composed of processor nodes is a place for data processing. Number of hidden layers and number of nodes in each hidden layer are usually determined using test and error method [1].

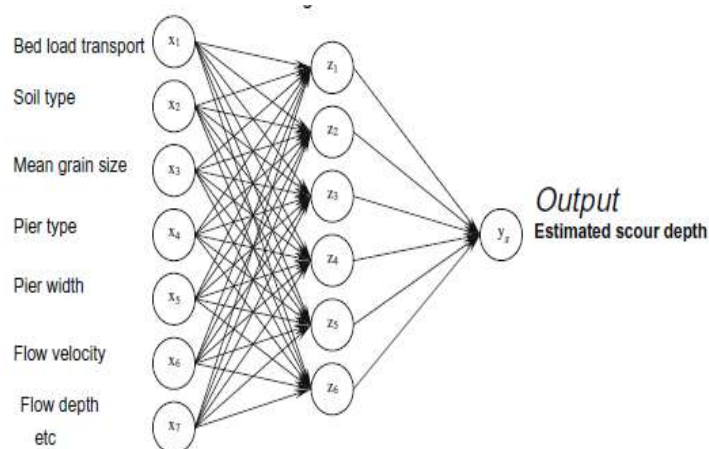


Figure (2): Artificial neural network

According to table 2 genetic programming (GP) had the least mean squares in the testing stage compared to neural network ANN and RBF.

Table (2): Comparing GP with neural networks

| Model | R^2 | RMSE | MAE |
|-------|-------|-------|---------|
| GP | 0.819 | 0.048 | -13.666 |
| ANN | 0.854 | 0.105 | -56.45 |
| RBF | 0.69 | 0.59 | 0.56 |

5 - Analyzing local scour around a pier in GP model:

Scour depth balance around a circular pier in uniform flow on a uniform, spherical bed and non-adhesive sediments depends on the group number of descriptive flow variables, sediment characteristics and basic geometry. Balance of local scour depth d_s around bridge pier is influenced by flow features, bed sediments and basic geometry. Below, the relationship of scour depth balance which is a function of effective parameters has been demonstrated.

$$(3) d_s = f(v, y, d_{50}, \sigma, b, l, g)$$

In which g = gravity acceleration. The previous works of researchers ([6], [17]) have achieved the outcome that categorizing variables without dimension produces better results. Below, the relationship between the normalized scour depth and flow depth in terms of dimensionless parameters has been offered.

$$(4) \frac{d_s}{y} = f(Fr, b/y, d_{50}/y, l/y, \sigma)$$

6 - Downstream Scour of Bucket Overflow

Flood water is disposed through overflow which is placed in the dam. Various types of overflows exist and the bucket overflow shape is usually used more. Figure 3 [7].

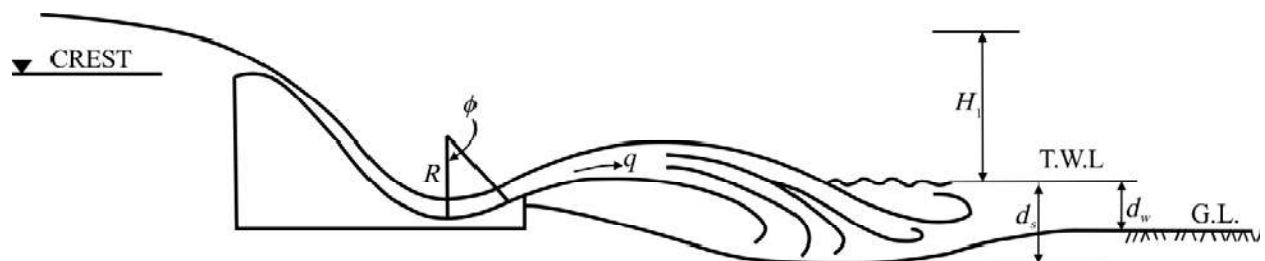


Figure (3): Scour of bucket overflow

Coalition in such overflows is in the shape of water jet plane. This means that surface water leaves the overflow and is thrown into the air and then plummets into downstream. The flow in downstream overflow has a very great velocity. Energy dissipation structures are utilized to prevent physical effects of this flow [18]. The three most common energy dissipation structures are quiet cubs, in which the flow energy dissipation is achieved using hydraulic jump, trundling bucket, in which the excess energy is dissipated by creating rotational flow and trundling water. Jumping flow, in which water flow is shot using ski jump similar to a jet towards downstream of the dam in order to reduce the erosive effects on the dam and important structures around the dam.

MomeniVesalin et al. [19], investigated the scour caused by rectangular jets in downstream of bucket-shaped projectiles and introduced flow intensity as the most effective parameter in the scour phenomenon in which coastal depth has a reverse effect on the scour depth. Ranjbar et al. [20], examined the temporal changes of downstream scour cavity of free falling jets and demonstrated that with the passage of time the scour cavity dimension would increase while cavity dimension increase rate would decrease. LashkarAra et al. [21], predicted the downstream scour of shooting buckets using neural networks. Bahrami and Barani [22] examined air density changes in passing flows from chute as a numeric model.

Various hydraulic, morphologic and geotechnical factors exist in scour depth (d_s) called discharge intensity (Q), collapse height (H_1), bucket radius (R), edge angle (φ), rock type, rock uniformity grade (rock homogeneity), time and overflow procedure. Figure 1. In the whole period, many investigations of physical formulae based on laboratory and observatory results have been done to estimate downstream

scour depth of the overflow. Below, some good formulae for the prediction of overflow scour depth have been demonstrated [6]:

Veronese formula (provided by USBR):

$$(5) \quad d_s = 1.90q^{0.54}H^{0.225}$$

Wu's formula:

$$(6) \quad \frac{d_s}{H_1} = 2.11\left(\frac{q}{qH_1^3}\right)^{0.51}$$

Martin's formula:

$$(7) \quad d_s = 1.5q^{0.6}H_1^{0.1}$$

GP Model in Downstream Scour of Bucket Overflow

GP model (GPLAB) in relation with border walls in MATLAB software was utilized to study the downstream scour of bucket overflow. Using the previous experiences categorizing variables achieved great results. The input parameter name of Froude number was $(q/(gH_1^3)^{0.5})$ and output parameter of relative scour depth was $(q/(gH_1^3)^{0.5})$. Five operators, addition, subtraction, multiplication, division and energy were used to find optimal formulation. A great number of generations needed the formula with the least error. The first maximum was divided from the tree and branch length [6].

GP Model Development:

GP is a branch of genetic algorithm (GA) and a method to best learn computer programs through learning artificial calculations for stick amount of population including examination of known accidental members of chromosomes and adaptability of each chromosome with a ratio for a purpose amount. Darwinian principle of natural selection has been used for healthier choice and reproduction. GP creates long equal or unequal computer programs including variables and several mathematical operator (function) sets as solution. Function set of system can be the purpose of calculating operations (+, -, *, /) and function such as exponential, trigonometric, logarithmic functions. Each function implicitly includes a transfer of a variable which assists the usage of several output programs in GP, while in GP based on tree such effects have been included [23].

GP used in this study uses two points of root intersections. Part of accidental situation and accidental length in selection is both parents and the interaction between them. If one of the children transgresses the maximum length, intersection would be left and restart by exchanging an equal part [23].

An operator from a structure with a leap inside another symbol on the same set has been altered.

GP adaptability may be calculated using the following formula:

(8)

In which X_j = efficiency level by one chromosome for the adaptability of J case and Y_j = the amount expected for the adaptability case of J.

In GP maximum size of preventing high growth programming with no restriction has been normally set [23]. This configuration has been tested for GP model objective finding coefficients.

To this day, applying GP has been limited in hydraulic engineering. Davidson [24], and Babovic and Keijzer [25] respectively determined physical relationships for friction (erosion) in turbulent pipe flow and additional resistance for the flow caused by flexibility of vegetation. Keijzer and Babovic utilized derivative physical equations in the real world of hydraulic data [25]. Giustolisi [26] determined chezy resistance coefficients in corrugated metal pipe. Giustolisi [27] discovered a better relationship between temporal pattern of flow string and sediment movement using field information and numeric model results. Azamathulla predicted bridge pier scour in 2010 [28].

GP model was expanded using similar input variables with an ANN-RBF model. Five of the ten parameters of equation 1, namely, fluid density, buoyant density sedimentation, dynamic viscosity fluid, gravity acceleration, energy line slope are fixed in all the tests. Therefore, the first compound includes 4 of the ten

parameters of equation 1 as the input and scour depth balance as the output. The second compound includes 6 parameters without dimension of equation 2 and scour depth normal balance as the input and output patterns respectively [6].

9 - Parameters of Statistical Errors

Statistical error parameter coefficient of determination (R^2), mean absolute percentage error (MAPE), and root-mean-square error (RMSE) were used in order to evaluate the training and testing stage.

$$(9) R^2 = 1 - \frac{\sum_{i=1}^N (O_i - t_i)^2}{\sum_{i=1}^N (O_i - \bar{O}_i)^2}$$

$$(10) RMSE = \sqrt{\frac{\sum_{i=1}^N (O_i - t_i)^2}{N}}$$

$$(11) MAPE = \frac{\sum_{i=1}^N |O_i - t_i|}{N}$$

$$(12) \delta = \frac{\sum |O_i - t_i|}{\sum O_i}$$

In which t_i determines the purpose amount from equal scour depth whilst O_i and \bar{O}_i levels are, respectively, the observed amounts and the average observed amounts from equal scour depth.

In table number 3, statistical errors for GP model were demonstrated at the testing stage for the estimation of scour depth of three hydraulic structures (pipeline, bridge pier, bucket overflow).

Table number (3): GP model for three structures, overflow, bridge pier and pipeline

| δ | MAE | Test | | structures |
|----------|---------|--------|-------|-------------|
| | | RMSE | R^2 | |
| 10.45 | 1.426 | 0.0957 | 0.741 | Pipeline |
| 26.262 | -13.666 | 0.048 | 0.819 | Bridge Pier |
| 0.177 | - | 0.861 | 0.977 | Overflow |

Conclusion

Problem of scour is a significant issue in water engineering and hydraulic structures. In recent years, many studies were done in this field and good results reached. In this study, the accuracy and application of GP model, first undertaken by Azmathullah on the three structures of bucket overflow, bridge pier and pipeline, were examined and compared together. These studies demonstrated that genetic programming model, in the testing stage, has a higher coefficient of determination ($R^2 = 0.977$) for lateral overflow, i.e. there is better correlation among data; While this model has a lower coefficient of determination ($R^2 = 0.741$) for the prediction of scour depth below pipeline. In the root-mean-square error (RMSE) part, GP model shows less error for the prediction of bridge pier scour depth. In bridge pier, the GP model has the least mean-square error. When GMDH model is taught with genetic programming, the outcome has higher coefficient of determination.

REFERENCES

1. Rafat, Abolfazl, Examining and Comparing Methods of Bridge Pier Scour Depth Estimation, 2nd National Conference of Architecture, Restoration, Urbanization and Sustainable Environment, HamedanShahidMofateh University, 04 Oct, 2014.
2. Chiew, Y. M. 1991 "Prediction of maximum scour depth at submarine pipelines." J. Hydraul. Eng., 117_4, 452-466.
3. Chao, J. L., and Hennessy, P. V. 1972, "Local scour under ocean outfall pipe-lines." J. Water Pollut. Control Fed., 44_7, 1443-1447
4. Kjeldsen, S. P., Gjørsvik, O., Bringaker, K. G., and Jacobsen, J. 1973 "Local scour near offshore pipelines." Proc., 2nd Int. Conf. on Portland Ocean Engineering under Arctic Conditions, Univ. of Iceland, Reykjavik, 308-331
5. Ibrahim, A., and Nalluri, C. 1986. "Scour prediction around marine pipelines." Proc., 5th Int. Symp. On Offshore Mechanics and Arctic Engineering, American Society of Mechanical, 679-684.
6. Azmathullah, H. Md., Deo, M. C., and Deolalikar, P. B. 2005. "Neural networks for estimation of scour downstream of ski-jump bucket." J. Hydraul. Eng., 131_10, 898-908
7. Azamathulla, H. Md., Deo, M. C., and Deolalikar, P. B. 2008. "Alternative neural networks to estimate the scour below spillways." Adv. Eng. Softw., 39_8, 689-698.
8. Azamathulla, H. Md., Ghani, A. A., M.ASCE, 2010. "Genetic programming to predict River pipeline." J. Hydraul. Eng., 136_3, 165-169.
9. Moncada-M., A. T., and Aguirre-Pe, J. 1999. "Scour below pipeline in river crossings." J. Hydraul. Eng., 125_9, 953-958

10. Melville, B. W., and Coleman, S. E. _2000_. *Bridge scour, Water Resources, Highlands Ranch, Colo.*
11. Johnson, P. A. _1995_. "Comparison of pier-scour equations using field data." J. Hydraul. Eng., 121_8_, 626–629.
12. Mohamed, T. H., Noor, M. J. M. M., Ghazali, A. H., and Huat, B. B. K. 2005. "Validation of some bridge pier scour formulae using field and laboratory data." American Journal of Environmental Science, 1_2_, 119–125.
13. Laursen, E. M., and Toch, A. _1956_. "Scour around bridge piers and abutments." Bulletin no. 4, Iowa Road Research Board, Ames, Iowa.
14. Melville, B. W., and Sutherland, A. J. _1988_. "Design method for local scour at bridge piers." J. Hydr. Div., 114_10_, 1210–1226.
15. Jain, S. C., and Fischer, E. E. _1980_. "Scour around bridge piers at highflow velocities." J. Hydraul. Eng., 106_11_, 1827–1842
16. Bateni, S. M., Borghei, S. M., and Jeng, D.-S. _2007_. "Neural network and neuro-fuzzy assessments for scour depth around bridge piers." Eng. Applic. Artif. Intell., 20, 401–414.
17. Najafzadeh, M. 2012, *Group method of data handling to predict scour depth around vertical piles under regular waves*, pag 1-5.
18. [18] Tourzende Jaani, M, Effect of Flow Interference of Body Gap on Hydraulic leap Length in Downstream Highflow, MS DISS., Shahid Chamran University, 2011.
19. Momeni Vesalian, Reza, Scour caused by Rectangular Jets in Downstream of Bucket-Shaped Projectiles with non-Uniform Materials, 7th International River Seminar, Shahid Chamran University, 13 to 15 Feb, 2007, 2-5.
20. Ranjbar, H. R., Study of Temporal Changes of Downstream Scour Depth of Falling Jets, 7th International River Seminar, Shahid Chamran University, 13 to 15 Feb, 2007, 2-5.
21. Lashkar Ara, B., Study of Temporal Changes of Downstream Scour Depth of Shooting Bucket Overflow Using Neural Network, 3rd Water Resources Management Conference, Tabriz University, 2009, 23-25.
22. Bahrami, A. and Barani, Q. A., Numeric Study of Air Density Changes in Passing Flows from Chute, 8th International Civil Engineering Congress, Shiraz University, 11-13 May, 2011.
23. Brameier, M., and Banzhaf, W. _2001_. "A comparison of linear genetic programming and neural networks in medical data mining." IEEE Trans. Evol. Comput., 5, 17–26.
24. Davidson, J. W., Savic, D. A., and Walters, G. A. _1999_. "Method for identification of explicit polynomial formulae for the friction in turbulent pipe flow." J. Hydroinform., 1_2_, 115–126.
25. Babovic, V., and Keijzer, M. _2000_. "Genetic programming as a model induction engine." J. Hydroinform., 2_1_, 35–60.
26. Giustolisi, O. _2004_. "Using genetic programming to determine Chèzy resistance coefficient in corrugated channels." J. Hydroinform., 6_3_, 157–173.
27. Giustolisi, O. _2004_. "Using genetic programming to determine Chèzy resistance coefficient in corrugated channels." J. Hydroinform., 6_3_, 157–173.
28. Azamathulla, H. Md., Ghani, A. A., Zakaria, N. A., and Aytac, G. 2010 "Genetic programming to predict bridge pier scour." J. Hydraul. Eng. 169–165, 1363 .