© 2013, Scienceline Publication

Journal of Civil Engineering and Urbanism

Volume 3, Issue 5: 292-299 (2013) (Received: July 20, 2013; Accepted: September 06, 2013; Published: September 30, 2013) ISSN-2252-0430

Estimation of Suspended Sediment Load Using Genetic Expression Programming

Zeinab Sheikhalipour[1*] and Farzad Hassanpour[2]

[1]*M. Sc. Student of Irrigation and Drainage, Soil and Water Faculty, University of Zabol, Zabol, Iran*
[2] *Department of Water Engineering, Soil and Water Faculty, University of Zabol, Zabol, Iran*

*Corresponding author's Email address: z_sh_ir@yahoo.com

ABSTRACT: Accurate estimation of suspended sediment load carried by a natural river is important for river engineering and water resources projects. In recent years, using smart systems to increase accuracy of estimating of river sediments are common. In this study were used the Genetic Expression Programming (GEP) in order to estimate suspended sediment load in *Sistan* River. Root mean square error (RMSE), mean bias error (MBE) and determination coefficient (R^2) statistics are used for evaluating the accuracy of the models. GEP is found that scenario 3 with four function and RMSE=0, MBE=2.69×10^{-4}, R2=1 in train period and RMSE=0, MBE=2.4×10^{-4} and R^2=1 in test period are superior in estimating suspended sediment load as the best accurate model. The modeling approach presented in this paper can be potentially used to reduce the frequency of costly operations for sediment measurement where hydrological data is readily available.Also estimation of suspended sediment load using other AI methods such as Particle Swarm Optimization, Tabu Search in *Sistan* River are suggested.

Keywords: Genetic Expression Programming (GEP), Artificial Intelligence (AI), Statistic Indicators, Suspended Sediment Load.

ORIGINAL ARTICLE

INTRODUCTION

Data mining consists of the extraction of novel, useful and understandable knowledge from observed data. Artificial Intelligence (AI) techniques are being used in a wide variety of data mining applications. They are being used as regression and classification. The problem of regression is usually described as a process of induction of a data model of the system that will be capable of predicting responses of the system that have yet to be observed (Velickov and Solomatine, 2000; Zhou et al., 2002).

Predictions of some hydraulic variables such as the suspended sediment load are highly needed for the design of most hydraulic structures and river engineering plans.

Correct estimation of suspended sediment loads in streams is important for river engineering. All surface water reservoirs are designed to a volume known as "the dead storage" to accommodate the sediment income that will accumulate over a specified period called the economic life. The underestimation of sediment yield results in insufficient reservoir capacity. To achieve an appropriate reservoir design and operation it is mandatory to determine sediment yield accurately. In environmental engineering, if the particles also transport pollutants, the estimation of river sediment load has an additional significance (Guven and Kişi, 2011).

McBean and Al-Nassri (1988) examined the uncertainty in suspended sediment curves and concluded that the practice of using sediment load versus discharge is misleading because the goodness of fit implied by this relation is spurious. Instead of suspended sediment curves, they have recommended that the regression can be established between sediment concentration and discharge.

Artificial Intelligence (AI) systems are being used in a wide variety of simulation applications. The focus of this paper is evaluating mathematical function effects of genetic expression programming (GEP) for suspended sediment load modeling. Gene expression programming (GEP) is, like genetic algorithms (GAs) and genetic programming (GP), a genetic algorithm as it uses populations of individuals, selects them according to fitness, and introduces genetic variation using one or more genetic operators. The fundamental difference between the three algorithms resides in the nature of the individuals: in GAs the individuals are linear strings of fixed length (chromosomes); in GP the individuals are nonlinear entities of different sizes and shapes (parse trees); and in GEP the individuals are encoded as linear strings of fixed length (the genome or chromosomes) which are afterwards expressed as nonlinear entities of different sizes and shapes (Ferreira, 2001).

GP (Koza1992) has been applied to a wide range of problems in artificial intelligence, engineering and science applications, industrial, and mechanical models, but LGP has been rarely applied in engineering and science area. GP can be successively applied to areas where (1) the interrelationships among the relevant variables are poorly understood (or where it is suspected that the current understanding may well be wrong), (2)

To cite this paper: Z. Sheikhalipour and F. Hassanpour.2013. Estimation of Suspended Sediment Load Using Genetic Expression Programming. *J. Civil Eng. Urban.,3* (5): 292-299.
Journal homepage http://www.ojceu.ir/main/

finding the size and shape of the ultimate solution is hard and a major part of the problem, (3) conventional mathematical analysis does not, or cannot, provide analytical solutions, (4) an approximate solution is acceptable(or is the only result that is ever likely to be obtained), (5) small improvements in performance are routinely measured (or easily measurable) and highly prized,(6) there is a large amount of data, in computer readable form, that requires examination, classification, and integration (such as molecular biology for protein and DNA sequences, astronomical data, satellite observation data, financial data, marketing transaction data, or data on the World Wide Web) (Banzhaf et al., 1998).

It was observed that only a few studies existed in the literature related to the use of GP and GEP in the field of river engineering and water resources engineering. Babovic et al. (2001) applied GP to sedimentary particle settling velocity equations. Harris et al. (2003) studied on velocity predictions in compound channels with vegetated floodplains using GP. Dorado et al. (2003) studied on prediction and modeling of the rainfall-runoff transformation of a typical urban basin using artificial neural networks (ANNs) and GP. Giustolisi (2004) determined Chezy resistance coefficient in corrugated channels by using GP.

Rabunal et al. (2007) determined the unit hydrograph ofa typical urban basin using GP. Only two studies were observed for sediment modeling using GP approach; Babovic (2000) used experimental flume data utilized by Zyserman and Fredsoe (1994) and expressed a new formulation forbed concentration of suspended sediment. Kizhisseri et al. (2005) used GP methodology to explore a better correlation between the temporal pattern of fluid field and sediment transport by utilizing two datasets; one from numerical model results and other from Sandy Duck field data.

The purpose of this study is to develop a mathematical model for estimation of suspended sediment load based on GP. Aytek and Kişi (2008) develop an explicit model based on genetic programming. Their research's results indicated that the proposed GP formulation performs quite well compared to sediment rating curves and multi linear regression models and is quite practical for use. Cobaner et al. (2009) is compared the potential of neuro-fuzzy technique with those of the three different artificial neural network technique. The comparison results shown the neuro-fuzzy models perform better than the other models in daily suspended sediment concentration estimation for the particular data sets. Azamathulla et al. (2010) used GP to predict bridge pier scour, and Singh et al. (2010) estimated the mean annual flood in Indian catchments by using a tree-based version of genetic programming: M5 tree model. Only three studies were observed for sediment modeling using GP approach. Kisi and Guven (2010) estimated suspended sediment concentration in two stations in USA using LGP.

The main purpose of this paper illustrates the mathematical functions effects in estimation of suspended sediment load using GEP in Sistan River, Iran. To achieve this goal, as well as used easily accessible metrological parameters.

MATERIALS AND METHODS

Location of the study area

Sistan plain area is 15000 Km^2 and locates in north of Sistan and Baloochestan province of Iran and has 2 cities, 6 parts, 6 townships and 937 villages. Its population estimated about 420000 persons in 2008 which half of them work in agricultural and domesticated fields. Climate of region evaluated totally dry. Mean annual precipitation is 52.3 mm and in fully rain years this rate reaches to 120 mm rarely and in dry year there is no precipitation (such as 9 mm for water year 2001-2002). This little precipitation makes impossible any kind of dry farming. Even regional natural vegetations, seldom grow, if do not locate near ground water. In this condition only an external water resource could make alive region and Hirmand Trans Boundary River has such role. Totally could say environment of Sistan is very vulnerable and depends on Hirmand River (Najafi and Vatanfada, 2011).

Hirmand River is an evident example of a flow of endorheism from an endorheic region. After passing a distance of about 1100 km, The river is divided into two main branches of Paryan Moshtarek and Sistan at a place called Jarikeh bordering Iran and Afghanistan. As one of two main branches of the Hirmand River, Sistan River is the main source of water in Sistan which is responsible for 70 percent of irrigated farmland in Sistan plain. The general slope of the river is about 0.2- to 0.6-thousandt. Important structures such as channel feeder, Kohak dam, Zahak-Niatak flood barrier, Zahak dam, Hedris canal, Sistan dam, Nohoorab Bridge and numerous irrigation channels, several villages and also the city of Zabol are located along the river, each of which has a significant impact on hydraulic process of the river. Sistan River is rare among the world's rivers because concentration of the suspended load of the river's flood flow varies mainly from 10 to 50 grams per liter. Low slope of the Sistan River's bed makes it prone to sedimentation; and on other hand, the negative effects of building Zahak and Kohak dams have sparked and increased the sedimentation. The particles forming the riverbed are very fine, and are mostly in the range of fine sand, clay and silt. The average diameter of particles forming the bed is about 0.02 mm (Torabi et al, 2001). Figure 1 shows overview of the position of Sistan and its River.

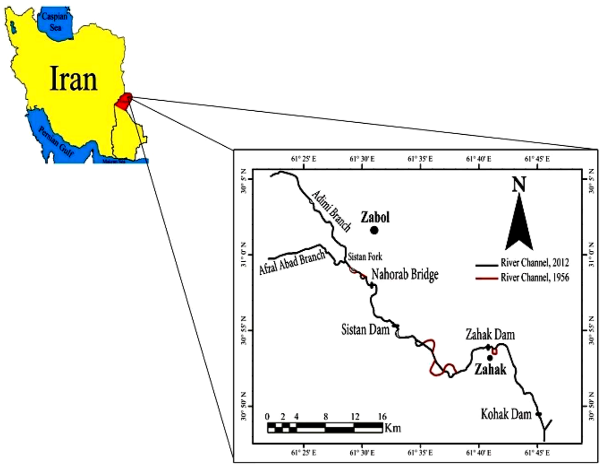

Figure 1. Position of Sistan region and plan of Sistan River

To cite this paper: Z. Sheikhalipour and F. Hassanpour.2013. Estimation of Suspended Sediment Load Using Genetic Expression Programming. *J. Civil Eng. Urban.*,*3* (5): 292-299.
Journal homepage: http://www.ojceu.ir/main/

Review of aerial photographs and satellite images of Sistan River plan in two intervals since 1956 show that the meanders of Sistan River have a lot of changes due to the construction of longitudinal and transverse structures, erosion and other similar natural process, and have created several deltas in some cases. These changes also now continue with the relocation, increase or sometimes reduction of sandy islands. For the reasons mentioned above and therefore the reduction of water flow and increase of the amount of sedimentation in the riverbed, these natural and permanent changes have intensified the speed of these developments.

Sediment rating curve

Whereas comprehensive data for river/stream flow are often readily available, measurements of suspended sediment concentration are commonly not of such high spatiotemporal resolution, making direct correlation problematical. The interpolation method most commonly employed to obtain high-resolution estimates for sediment loads is the so called rating curve, which is based on the close relationship between stream flow and sediment load (Einstein, 1943; Cohn et al., 1992; Phillips et al., 1999). A rating curve consists of a graph or equation relating sediment discharge or concentration to stream discharge, which can be used to predict sediment loads from the stream flow record. The sediment rating curve generally represents a functional relationship of the form:

$$Q_s = aQ^b \quad (1)$$

In which Q_s is suspended sediment discharge (ton/day), Q is stream flow (m^3/s), and a, b are coefficients estimated by means of logarithmic linear regression between log Q_s and log Q for a particular site. However, the rating curve method has several disadvantages, such as poorness of fit due to the common lack of frequent sediment sampling at gauging stations (Miller, 1951). Also, for improved fitting of the sediment rating curve, it is better that the data be normally distributed (Thomas, 1988), which is rarely the case.

Overview of Gene Expression Programming

Gene expression programming (GEP) is, like genetic algorithms (GAs) and genetic programming (GP), a genetic algorithm as it uses populations of individuals, selects them according to fitness, and introduces genetic variation using one or more genetic operators (Mitchell, 1996). The fundamental difference between the three algorithms resides in the nature of the individuals: in GAs the individuals are linear strings of fixed length (chromosomes); in GP the individuals are nonlinear entities of different sizes and shapes (parse trees); and in GEP the individuals are encoded as linear strings of fixed length (the genome or chromosomes) which are afterwards expressed as nonlinear entities of different sizes and shapes (i.e., simple diagram representations or expression trees).The flowchart of a gene expression algorithm (GEA) is shown in Figure 2.

The interplay of chromosomes (replicators) and expression trees (phenotype) in GEP implies an unequivocal translation system for translating the language of chromosomes into the language of expression trees (ETs). The structural organization of GEP chromosomes presented in this work allows a truly functional genotype/phenotype relationship, as any modification made in the genome always results in syntactically correct ETs or programs. Indeed, the varied set of genetic operators developed to introduce genetic diversity in GEP populations always produces valid ETs. Thus, GEP is an artificial life system, well established beyond the replicator threshold, capable of adaptation and evolution.

The advantages of a system like GEP are clear from nature, but the most important should be emphasized. First, the chromosomes are simple entities: linear, compact, relatively small, easy to manipulate genetically (replicate, mutate, recombine, transpose, etc.). Second, the ETs are exclusively the expression of their respective chromosomes; they are the entities upon which selection acts and, according to fitness, they are selected to reproduce with modification. During reproduction it is the chromosomes of the individuals, not the ETs, which are reproduced with modification and transmitted to the next generation.

On account of these characteristics, GEP is extremely versatile and greatly surpasses the existing evolutionary techniques. Indeed, in the most complex problem presented in this work, the evolution of cellular automata rules for the density-classification task, GEP surpasses GP by more than four orders of magnitude.

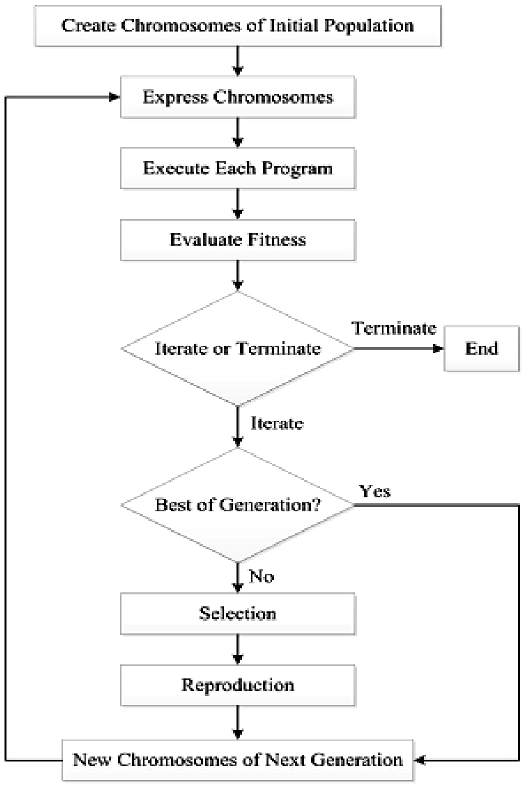

Figure 2. The flowchart of GEP, adapted from Mitchell, 1996.

Data normalization

One advantage is to avoid attributes in greater numeric range s dominating those in smaller numeric ranges, and another advantage is to avoid numerical difficulties during the calculation. It is recommended to linearly scale each attribute to the range [0.1, 0.9], [− 1, +1] or [0, 1]. In the modeling process, the data sets of

To cite this paper: Z. Sheikhalipour and F. Hassanpour.2013. Estimation of Suspended Sediment Load Using Genetic Expression Programming. *J. Civil Eng. Urban.*,3 (5): 292-299.
Journal homepage http://www.ojceu.ir/main/

maximum and minimum temperature, streamflow, and suspended sediment load were scaled to the range between 0 and 1 as follow:

$$N_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad (2)$$

where N_i is the normalized value, x_i is the original data and x_{min}, x_{max} are, respectively, the minimum and maximum of the original data.

Error functions

Measures of goodness of fit between observed and predicted datasets are based on the coefficient of determination, R^2, as well as the three measures defined below:

– Root mean squared error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{t}(P_i - O_i)^2}{t}} \qquad (3)$$

– Mean bias error (MBE):

$$MBE = \frac{\sum_{i=1}^{t}(P_i - O_i)}{t} \qquad (4)$$

where P_i and O_i are the simulated and observed values respectively, and t the sample size. R^2 each vary between 0 and 1; the closer the values are to 1, the better is the goodness of fit. Goodness of fit improves as the RMSE approaches 0, and as the MBE decreases.

RESULTS AND DISCUSSION

Rating Curve

One of the most common methods for estimating of suspended sediment load is using sediment rating curve in rivers. This curve typically is defined as an exponential relationship between water flow and sediment discharge ($Q_s = a.Q^b$).

The seasonal and annual sediment rating curves were plotted. The seasonal "a" and "b" coefficients and R2 values have been shown in Table 1. Sediment rating curve diagram for spring, summer, fall, winter and also annual sediment rating curves are shown in Figure 3, respectively. The annual sediment rating curve with a=13.85 and b=1.574 is allocated to the highest determination coefficient (R^2=0.787).

The statistical parameters of the streamflow and sediment data for the river station are given in Table 2. In the table, the x_{mean}, S_x, C_v, C_{sx},x_{max} and x_{min} denote the mean, standard deviation, coefficient of variation, skewness, maximum and minimum, respectively.

Table1. Seasonal a, b and determination coefficients for sediment rating curve

Season	a	b	R^2
Spring	7.619	1.686	0.783
Summer	14.79	1.515	0.694
Fall	35.8	0.852	0.338
Winter	9.469	1.809	0.783
Annual	13.85	1.574	0.787

Table 2. The Statistical parameters of data set for the Sistan River station (1996-2012)

Period	No. of data	Data Type	X_{mean}	S_x	C_v (S_x/X_{mean})	C_{sx}	X_{max}	X_{min}	X_{max}/X_{min}
Spring	207	Flow ($m^3\ s^{-1}$)	62.56	71.37	1.14	2.48	488.59	1.44	338.59
		Sediment (ton day^{-1})	22435.30	58842.84	2.62	5.50	577483.22	31.88	18115.93
Summer	81	Flow ($m^3\ s^{-1}$)	6.15	5.31	0.86	2.62	34.45	0.28	123.03
		Sediment (ton day^{-1})	757.56	3058.75	4.04	7.51	26119.70	1.71	15275.33
Fall	65	Flow ($m^3\ s^{-1}$)	6.62	6.75	1.02	2.02	32.50	0.20	166.67
		Sediment (ton day^{-1})	692.19	2491.27	3.60	5.47	16202.51	2.98	5430.46
Winter	222	Flow ($m^3\ s^{-1}$)	23.98	35.46	1.48	3.23	227.60	0.52	440.23
		Sediment (ton day^{-1})	17752.86	56657.48	3.19	4.48	390899.81	1.98	197523.62
Annual	576	Flow ($m^3\ s^{-1}$)	33.39	53.37	1.60	3.47	488.59	0.20	2505.59
		Sediment (ton day^{-1})	15115.82	50549.20	3.34	5.79	577483.22	1.71	337723.92

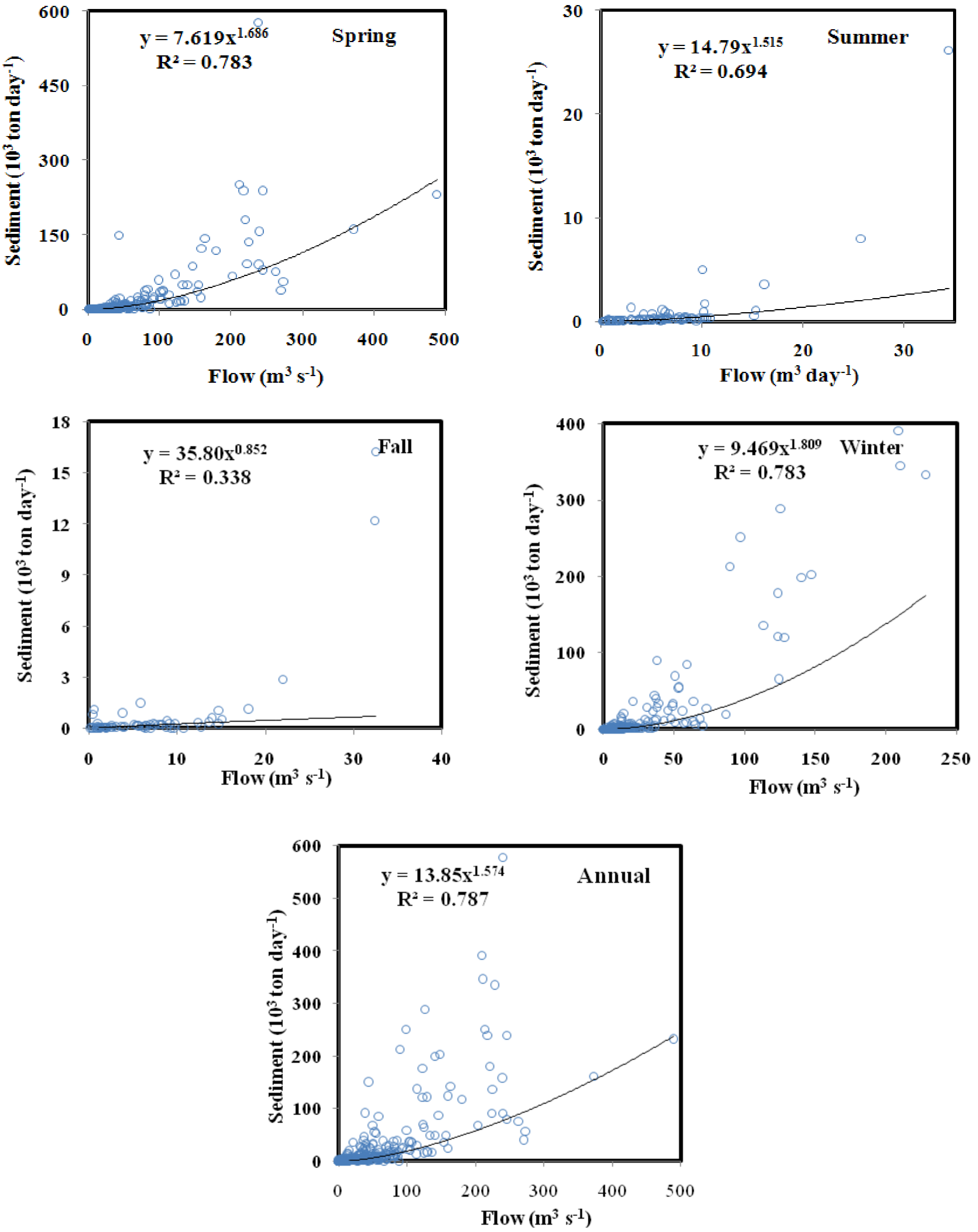

Figure 3. Seasonal and annual sediment rating curve in Sistan River

Gene expression programming

In this study, 2315 data were used to estimate suspended sediment load. This data relating to be 1996 to 2012 the Sistan River hydrometric station. Three GEP models were considered, based on three different types of inputs: (1) Q and T_d, (2) Q, T_{min} and T_{max}, and (3) Q, T_{min}, T_{max}, T_d and Q_c, corresponding to scenario 1, scenario 2 and scenario 3, respectively (Table 3). Q, T_{min}, T_{max}, T_d and Q_c represent the stream flow, minimum temperature, maximum temperature, T_{max}-T_{min} and classified sediment flow, respectively.

In each scenario, five series of arithmetic operators and mathematical functions were used to suspended sediment load modeling (Table 4).

Table 3. Combinations of input models in GEP scenarios

Scenario	Input combinations
1	Q , T_d
2	Q , T_{min} , T_{max}
3	Q , T_{min} , T_{max} , T_d , Q_c

Table 4. Mathematic functions used for models in GEP scenarios

Functions series	arithmetic operators and basic mathematical functions
A	+ . - , * , /
B	+ . - , * , / , Exp(x)
C	+ . - , * , / , √
D	+ . - , * , / , Exp(x) , ln(x) , √
E	+ . - , * , / , Exp(x) , ln(x) , √ , Sin(x) , Cos(x) , Tan(x)

Scenario 1

In scenario 1, Q and T_d are input and Q_s is output. The results of five series of mathematical functions were analyzed using RMSE, MBE and R^2 statistical indicators. In this scenario, the Gene expression programming model with set functions E, RMSE=0.04, MBE=1.26×10^{-2} and R^2=0.74 has the best results (Figure 4,a). Then function series D, A, C and B are the next priorities, respectively (Table 5).

Scenario 2

In scenario 2, Q, T_{min} and T_{max} are input and Q_s is output. The results of five series of mathematical functions were analyzed using RMSE, MBE and R^2 statistical indicators. In this scenario, the Gene expression programming model with set functions D, RMSE=0.03, MBE=1.35×10^{-2} and R^2=0.83 has the best results (Figure 4,b). Then function series B, C, A and E are the next priorities, respectively (Table 5).

Scenario 3

In scenario 3, Q T_{min}, T_{max}, T_d, Q_c are input and Q_s is output. The results of five series of mathematical functions were analyzed using RMSE, MBE and R^2 statistical indicators. In this scenario, Q_c much causal effect is evident, as regardless of mathematical functions used for scenario using each mathematical function series is a good solution. Therefore, Q_c reduce mathematical parameters effects. In this scenario, based on statistical analysis, the Gene expression programming model with set functions A, RMSE=0, MBE=2.69×10^{-4} and R^2=1 has the best results (Figure 4,c). Then function series D, E, B and C are the next priorities, respectively (Table 5).

Statistic indicators to help evaluating performance of different models are RMSE, MBE and R^2. These statistic indicators can be valuable when the models to find which between observed values and predicted values are calculated. According to RMSE, MBE and R^2 values show a comparative advantage models.

Table 5. Train and test results for GEP scenarios

Scenario	Functions	Train			Test		
		R^2	RMSE	MBE	R^2	RMSE	MBE
1.00	A	0.73	0.04	1.55×10^{-2}	0.54	0.02	8.87×10^{-3}
	B	0.74	0.35	1.29×10^{-2}	0.53	0.02	6.4×10^{-3}
	C	0.73	0.04	1.61×10^{-2}	0.46	0.02	1.01×10^{-2}
	D	0.73	0.04	1.49×10^{-2}	0.52	0.02	8.48×10^{-3}
	E	**0.74**	**0.04**	$\mathbf{1.26\times10^{-2}}$	**0.45**	**0.02**	$\mathbf{6.67\times10^{-3}}$
2.00	A	0.82	0.03	1.48×10^{-2}	0.56	0.02	9.65×10^{-3}
	B	0.82	0.03	1.33×10^{-2}	0.60	0.02	7.27×10^{-3}
	C	0.82	0.03	1.41×10^{-2}	0.53	0.02	9.46×10^{-3}
	D	**0.83**	**0.03**	$\mathbf{1.35\times10^{-2}}$	**0.58**	**0.02**	$\mathbf{8.18\times10^{-3}}$
	E	0.81	0.03	1.41×10^{-2}	0.58	0.02	8.23×10^{-3}
3.00	**A**	**1.00**	**0.00**	$\mathbf{2.69\times10^{-4}}$	**1.00**	**0.00**	$\mathbf{2.4\times10^{-4}}$
	B	1.00	0.00	3.85×10^{-4}	1.00	0.00	3.71×10^{-4}
	C	1.00	0.00	5.44×10^{-4}	1.00	0.00	4.27×10^{-4}
	D	1.00	0.00	3.53×10^{-4}	1.00	0.00	3.07×10^{-4}
	E	1.00	0.00	3.83×10^{-4}	1.00	0.00	3.65×10^{-4}

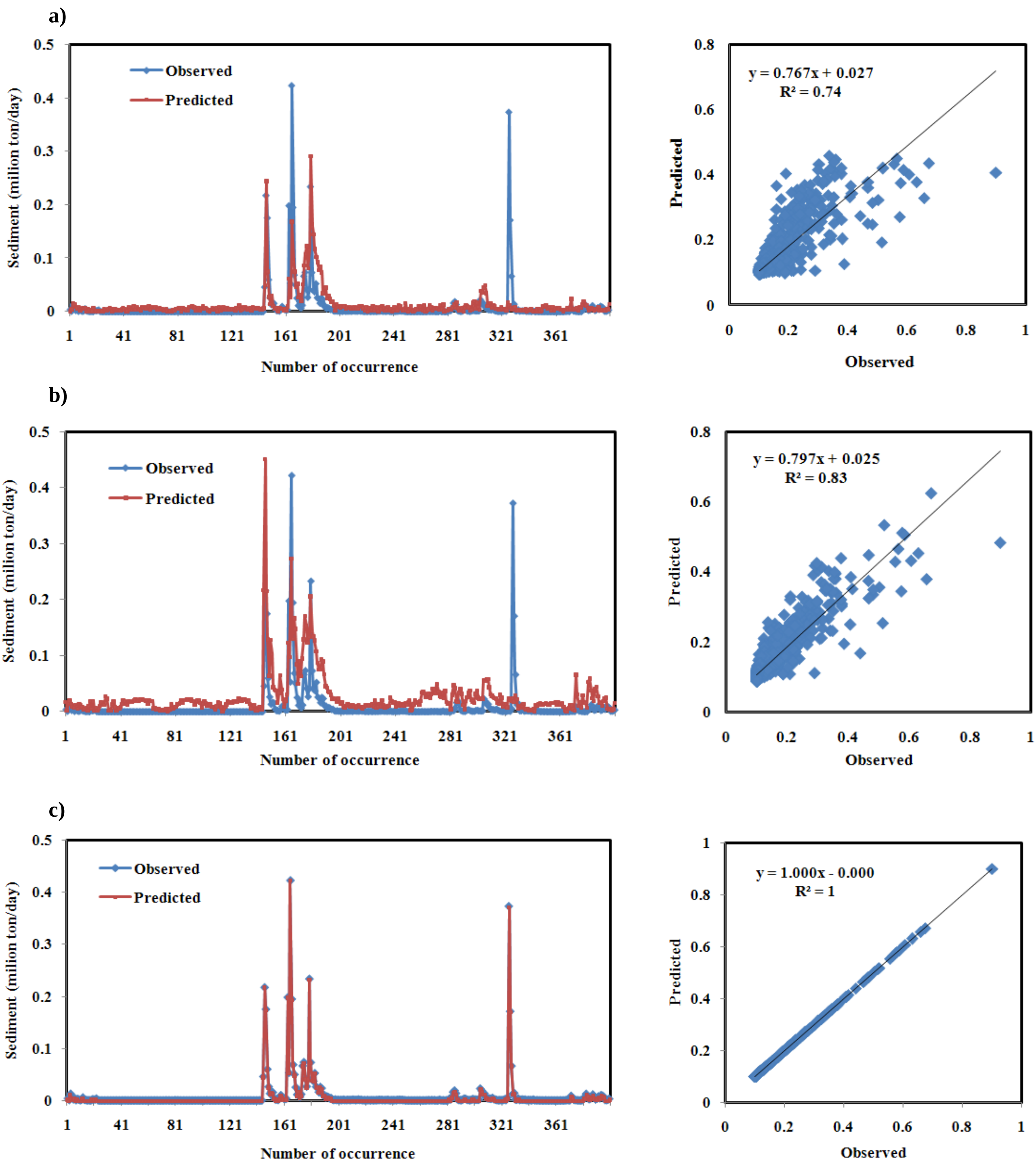

Figure 4. The observed and predicted suspended sediment load in Sistan River, a: best model of scenario 1, b: best model of scenario 2, c: best model of scenario 3

According to the results, square mathematical function plays affect role in estimation of suspended sediment load, but reduce its role with increasing other functions. Exponential function effect is more pronounced with increasing number of inputs in estimation of suspended sediment load, and can be said in scenario 1 with two inputs, had negative impact on final results.

Increasing mathematical functions of the models are low inputs more effective than models that have a high number of entries. In other words, impact of increasing number of entries is less than increasing mathematical functions.

According to the results, mathematical parameters effects in estimating of suspended sediment load is undeniable, but it is important to have a large impact when number of inputs is minimal. In any case, the influence of effective input parameters is much more than as mathematical functions.

CONCLUSION

This paper reports the evaluation of mathematical functions effects in estimation of suspended sediment load using genetic expression programming in Sistan River, Iran.

To cite this paper: Z. Sheikhalipour and F. Hassanpour.2013. Estimation of Suspended Sediment Load Using Genetic Expression Programming. *J. Civil Eng. Urban.*,3 (5): 292-299.
Journal homepage http://www.ojceu.ir/main/

The model gives a practical and mathematical way for suspended sediment load estimation to obtain accurate results and encourages use of GEP in other aspects of water engineering studies. The suspended sediment estimates based on GEP models are compared sediment rating curves. The results obtained with GEP models are better than those obtained using the conventional rating curve and confirm the ability of this approach to provide a useful tool in solving specific problems in river engineering, such as suspended sediment load estimation. The results suggest that the GEP approach may provide a superior alternative to the sediment rating curve.

In the present study, genetic expression programming that is a generalization of genetic algorithms was used for the explicit formulation of suspended sediment load by arithmetic operators and basic mathematical functions. Other optimization techniques such as Ant Colony, Artificial Fish Swarm, Bee Algorithm, Cuckoo Optimization Algorithm, Imperialist Competitive Algorithm, Particle Swarm and Tabu Search, may also be used for the derivation of formulas instead of genetic programming and their accuracies may be compared with each other.

The last conclusion introduces designed GEP models to set of different functions to estimating the Sistan River suspended sediment load using multiple inputs.

REFERENCES

1. Aytek A, Kisi O. (2008). A genetic programming approach to suspended sediment modeling. J Hydrol 351(3–4):288–298.
2. Azamathulla HMd, Ghani AAb, Zakaria NA, Guven A. (2010). Genetic programming to predict bridge pier scour. J HydraulEng 136(2):165–169.
3. Babovic, V. (2000). Data mining and knowledge discovery in sediment transport. Comput.-Aided Civ. Infrastruct. Eng. 15(5), 383–389.
4. Babovic V, Keijzer M, Aguilera, DR, Harrington J. (2001).Automatic Discovery of Settling Velocity Equations. D2K Technical Report, D2K-0201-1.
5. Banzhaf W, Nordin P, Keller RE, Francone FD. (1998). Genetic programming. Kaufmann, San Francisco.
6. Cobaner M, Unal B, Kisi O. (2009). Suspended sediment concentration estimation by an adaptive neuro-fuzzy and neural network approaches using hydro-meteorological data. J Hydrol 367(1– 2):52–61.
7. Dorado J, Rabunal JR, Pazos A, Rivero D, Santos A, Puertas J. (2003). Prediction and modelling of the rainfall-runoff transformation of a typical urban basin using ANN and GP. Appl.Artif. Intell. 17, 329–343.
8. Giustolisi O. (2004). Using genetic programming to determine Chezy resistance coefficient in corrugated channels. J. Hydroinform.,157–173.
9. Harris EL, Babovic V, Falconer RA. (2003). Velocity predictionsin compound channels with vegetated floodplains using genetic programming. Int. J. River Basin Manage. 1 (2), 117–123.
10. Kizhisseri AS, Simmonds D, Rafiq Y, Borthwick M. (2005). An Evolutionary computation approach to sediment transport modeling .In: Fifth International Conference on Coastal Dynamics,April 4–8, 2005, Barcelona, Spain.
11. Koza JR (1992) Genetic programming: on the programming of computers by means of natural selection. MIT, Cambridge.
12. Rabunal JR, Puertas J, Suarez J, Rivero D. (2007). Determination of the unit hydrograph of a typical urban basin using genetic programming and artificial neural networks. Hydrol.Process. 21, 476–485.
13. Zyserman JA, Fredsoe J. (1994). Data analysis of bed concentration of suspended sediment. J. Hydr. Eng., ASCE 120 (9), 1021–1042.
14. Najafi A, Vatanfada J. (2011). Environmental Challenges in Trans-Boundary Waters, Case Study: Hamoon Hirmand Wetland (Iran and Afghanistan). *Int. J. Water Resources and Arid Environments*, 1, 16-24.
15. Torabi SA, Tajrishi M, Sarang SA, Burqa'ei SM. (2001). Sistan River hydraulic analysis of one-dimensional flow. *6Th Iranian Hydraulic Conference*, Tehran University, Iran, 13.
16. Mitchell M. (1996). An Introduction to Genetic Algorithms ,MIT Press.
17. Velickov S, Solomatine D. (2000). Predictive data mining: practical examples, in Proceedings of the Second Joint Workshop on Artificial Intelligence in Civil Engineering, pp. 1-17, Cottbus, Germany.
18. Zhou C, Xiao W, Tirpak T, Nelson P. (2002). Discovery of classification rules by using Gene Expression Programming, in Proceedings of the 2002 International Conference on Artificial Intelligence, pp. 1355-1361, Las Vegas.