Journal of Hydrosciences and Environment
Available online at http://jhe.usb.ac.ir/

ISSN: 2345-5608

Estimating Suspended Sediment Load in Rivers Using the Imperialist Competitive Algorithm

A. Heydari Tashekaboud[1]*, Sh. Heydari Tashekaboud[2]

1-Assistant Professor of Geography & Urban Planning, Faculty of Literature and Human Sciences, Ferdowsi University of Mashhad, Mashhad, Iran
2 Ph.D. Student of Water Engineering department, Faculty of Agriculture, University of Sari, Sari, Iran

A R T I C L E I N F O

Article history:

Received: *6 May 2019*
Accepted: *12 October 2019*

Keywords:
Fuzzy Logic,
Increasing Block Tariffs.
Water Consumption,
Iran.

A B S T R A C T

Erosion phenomenon and sediment transition are among the most complex hydrodynamics problems, so their governing equations cannot be determined easily. This paper used the Imperialist Competitive Algorithm (ICA) to predict the daily suspended sediment loads (SSLs) of the Zarinehrood River. The input was composed of SSL of the sedimentary station located in the Zarinehrood River during 2005-2015 (10 statistics years) with the flow discharge variable during this month. The results of implementing ICA showed the high accuracy of the ICA showing $R^2 = 0.89$ and RMSE = 235 mg/L. In general, the results obtained from the ICA used in this paper showed the high capability and accuracy of the ICA in estimating SSL of the Zarinhorod River consumption reforms.

1. Introduction

The sediment load of a basin, which passes through a certain section of the river, depends mainly on the climatic characteristics such as precipitation type, severity and temporal and spatial distribution, the characteristics of the upstream drainage basin, such as the type of soil, the type and status of vegetation, land use, morphology, slope, topography, the scope of the basin, and finally, the capacity of carrying sedimentary materials. Determining the amount of sediment carried by rivers is important in many aspects. The sediment carried by the water flow is considered to be an important factor in the formation of the geometric structure and the morphological characteristics of the rivers. According to Ozturk et al. (2001), any increase or decrease in sediment load of the rivers entails various consequences, such as the occurrence of degradation or aggradation phenomena, the changes in the granularity of the materials and the shape of the plate and its longitudinal profile. In order to manage the erosion and sedimentation and the stabilization of the bed and flood, awareness of the amount of sediment carried by the river and the effectiveness of protective measures is unnecessary. In general, it is important to measure sediment load of rivers in order to estimate the level of erosion and sediment of the drainage basin, reckon the useful life of dams, modify sediment load sampling methods, and estimate sediment content in water (Ozturk et al. 2001).

Recent studies in this field include Kalteh (2008), Kuok et al. (2010), Guo and Wang (2010), Gholami et al. (2015), Chen and Chau (2016), Kisi and Zounemat-Kermani (2016) and Buyukyildiz and Kumcu (2017). They have used artificial neural networks, genetic programming, and optimization algorithms to predict and estimate suspended sediments of the rivers.Kisi (2005) used the ANN method to model suspended sediment load (SSL) and compared the results with a sediment rating curve (SRC) and multivariate linear regression (MLR). Altunkaynak (2009) used a genetic algorithm to estimate the amount of sediment using discharge amounts. Mohammad Rezapour (2015) used a genetic algorithm to optimize the relationship between flow and sediment discharge for the Nodeh station located on the Gorganrood River. The results were compared by using an SRC. The evaluation of the results showed that the genetic algorithm had a higher accuracy than the SRC. Ebrahimi et al. (2013) investigated the performance of a honey-bee algorithm (HBA) in SSL and concluded that the HBA had high efficiency. Kisi and Shiri (2012) attempted to predict the SSL of the El River in California using daily precipitation, flow, and sediment concentration data by gene expression programming (GEP), neural network, and comparative fuzzy-neural deductive system methods. The results showed that the GEP method outperformed the other two methods in predicting daily SSL. Kakaei Lafdani et al. (2013) used two models of artificial neural network (ANN) and support vector machines (SVM) to forecast the DSS load of a river and compared the results with regression models. It was found that the regression models had weaker performance than the other two models in predicting sediment. Najaf Dizaji et al. (2013) predicted sediment in the Zarrinehrood river basin using an ANN and concluded that multi-layered perceptron (MLP) model with a regression coefficient of 0.92 at Qabblo station, the generalized feed forward (GFF) prediction model with a regression coefficient of 0.90 at the Sarigamysh station, and

* Corresponding author's email:
heydariakbar@um.ac.ir

the neural network model with a regression coefficient of 0.885 at the Ananian bridge Station performed better in sediment estimation. Ghorbani et al. (2013) estimated the sediment load by multivariate regression, ANN, and neuro-fuzzy methods. The results indicated the superiority of the ANN in this field. Heng and Suetsugi (2013) evaluated the ANN efficiency in estimating the sediment load of the Tonle Sap river basin, Cambodia. The results indicated the acceptable performance of the ANN in the field. Kumar Goyal (2014) examined the performance of the M5 model trees and wavelet regression compared to an ANN to predict sediment yield in the Nagua River drainage basin in India. The results showed the superiority of the M5 model trees and wavelet regression. Khorshiddoost et al. (2015) evaluated the potential of a fuzzy inference system model (ANFIS) to estimate suspended load sedimentation of the Zarrinehrood river and compared it with two types of ANN models. The results indicated the better performance of the ANFIS model in maximum suspended load estimation. Seutloali and Beckedahl (2015) dealt with the factors influencing rill erosion on roadcuts in the south eastern region of South Africa. In addition to identifying the slope, length, the percentage of vegetation, and soil texture as factors affecting erosion rate, it was concluded that the presence of vegetation and making a mild slope could have a negative effect on the amount of erosion. Liu and Beljadid (2017) presented a numerical model to determine the flow profile, sediment transport, and bed-form variations. The numerical model was based on the integration of hydrodynamic flow equations, sediment transport equation, sediment continuity equation, and simultaneous solving of combined matrices. Ebtehaj and Bonakdari (2016) predicted river sediment using an imperialist competitive algorithm (ICA) and a particle swarm optimization (PSO) algorithm. The results showed that the ICA was superior to the PSO algorithm in sediment prediction. Matos et al. (2018) predicted the daily suspended sediment of the Yangtze River using a new GPU programming technique inspired by the machine learning concepts. The results showed that the technique used to predict the amount of suspended sediment was very successful.

Most previous studies have investigated the application of ANNs, regression models, and empirical equations in this field and limited research has took advantage of new methods such as meta-heuristic algorithms to predict SSL. Due to the optimal efficiency of meta-heuristic algorithms with less cost and time to achieve an optimal response, the present study evaluates and compares the most robust meta-heuristic optimization algorithm including imperialist competitive algorithm (ICA) to predict suspended sediment load (SSL) of the Zarinehrood River in the south-east of Lake Urmia.

2. Materials and methods

2.1. Case Study

Zarinehrood is a river in Kurdistan province and West Azerbaijan province, Iran. It is 302 km long, originating from Zagros Mountains of Kurdistan province in the south of Saqqez, where it is also known as the Jaqatoo River. This basin is located between the longitudes of 45°45' and 47°15' E. and the latitudes of 35°30' and 36°45' N. The area of the Zarinehrood basin is about 13,890 km^2. The annual average precipitation of Zarinehrood drainage Basin is estimated to be 527 mm. The average annual temperature in the Zarinehrood dam is estimated to be -1.8°C, varying from -26.5°C in February to 5°C in August. Figure 1 depicts the location of the Zearinehrood River.

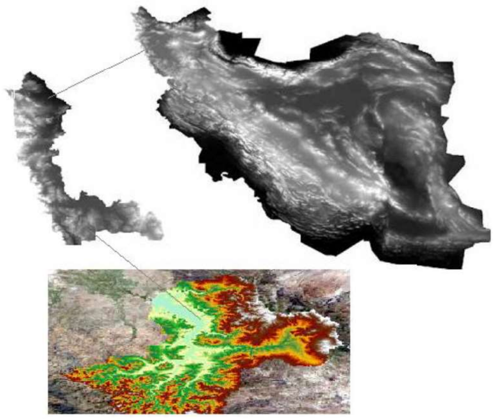

Fig. 1. Location of the Zarinehrood on the map

To calculate the sediment discharge by each of the models, the required statistics and data such as daily discharge and suspended sediment load (SSL) of the Sari-Qamish station at the Zarrineh River were first used from 2005 to 2015 as inputs, and the, the daily values of SSL were estimated. Data were collected from the West Azerbaijan Regional Water Agency (SSL and bed load were separated by the regional water authority). The daily statistical parameters of the Zarinehrood station used for the training and test periods are presented in Table 1.

Table 1. The daily statistical parameters of Zarrinehrood station for training and test periods

	Data Type	X	X_{min}	X_{max}	S_x	CS_x
Training data	Discharge	57	0.30	1022	121	5.12
	sediment	315	4	7251	734.2	5.94
Test data	Discharge	42	0.1	469	89	3.2
	sediment	286.9	2	7036	726.6	5.87

In Table 1, X_{min} is the minimum of data, X_{max} is the maximum of data, S_x is the standard deviation of data, and CS_x is the coefficient of data variations.

There should be sufficient assurance of the homogeneity of the data to make calculations. For this purpose, the homogeneity of the data was examined during the selected statistical period (Table 2). The results showed that the data were homogeneous in the Zarinehrood station.

Table 2. Homogeneity test results for used data

Variable	Risk of refuting null assumption (%)	Confidence level (a)	P-Value
Flow discharge	60.4	0.05	0.58
Sediment discharge	58.1	0.05	0.55
Precipitation	27.4	0.05	0.25

In this test, assumptions 0 and 1 express the homogeneity and heterogeneity of data, respectively. If the P-value is greater than the desired degree of confidence, the assumption 0 and otherwise the assumption 1 is acceptable. After ensuring homogeneity, two-thirds of the data (70% of the data) were used to train the model and the remaining one-third (30%) was used to test the obtained parameters using ICA.

2.2. Imperialist Competitive Algorithm (ICA)

Like other evolutionary ones, the proposed algorithm starts with an initial population (countries in the world). Some of the best countries in the population are selected to be the imperialists and the rest form the colonies of these imperialists. All the colonies of initial population are divided among these imperialists based on their power. The power of an empire, which is the counterpart of the fitness value in the GA, is inversely proportional to its cost. After dividing all colonies among imperialists, these colonies start moving toward their relevant imperialist country. The total power of an empire depends on both the power of the imperialist country and the power of its colonies. We will model this fact by defining the total power of an empire by the power of imperialist country plus a percentage of mean power of its colonies. Then, the imperialistic competition begins among all the empires. Any empire that is not able to succeed in this competition and cannot increase its power (or at least prevent the loss of its power) will be eliminated from the competition. The imperialistic competition will gradually result in an increase in the power of powerful empires and a decrease in the power of weaker ones. Weak empires will lose their power and ultimately they will collapse (Atashpaz-Gargari and Lucas 2007). The movement of the colonies toward their relevant imperialists along with competition among empires and also the collapse mechanism will hopefully cause all the countries to converge to a state in which there exists just one empire in the world and all the other countries are colonies of that empire. In this ideal new world, colonies have the same position and power as the imperialist (Atashpaz-Gargari and Lucas 2007).

The operation of the imperialist competitive algorithm is as follows:

- Initialize the empires
- Move the colonies toward their relevant imperialist (assimilation)
- Randomly change the position of some colonies (revolution)
- If there is a colony in an empire which has lower cost than the imperialist, exchange the positions of that colony and the imperialist.
- Unite the similar empires
- Compute the total cost of all empires
- Pick the weakest colony (colonies) from the weakest empires and give it (them) to one of the empires
- Eliminate the powerless empires

If there is just one empire, stop, if not go to 2.

2.3. Problem Definition

2.3.1. The objective function

The purpose of the study is to minimize the difference between the measured amounts of the observed sediment (Q_o) and the calculated amounts of the sediment (Q_m) using four algorithms. The desired objective function in this study is considered as Eq. (1):

$$g(u)=\sum_{i=1}^{l}\sqrt{(Q_m-Q_o)^2} \tag{1}$$

where *u* is the input factor and *g(u)* is the objective function. Input structures (to determine the proper input structures, using MATLAB software, some codes were written for each of the four algorithms, and after testing the codes, the best input structure was selected for the algorithms based on the statistical parameters mentioned in the previous section) used to predict the SSL of the Zarinehrood River are as follows:

$$Qr_t \tag{2}$$

$$Qr_t,\ Qr_{t-1} \tag{3}$$

$$Qr_t,\ Qr_{t-1},\ Sr_{t-1} \tag{4}$$

where Qr_t and Sr_t indicate the discharge and suspended sediment load in *t* days. In order to determine the appropriate input structures, the appropriate values were selected according to Table 3, including initial populations, the number of colonies, positive and negative advertisement, coalition rate, percent jump, to convey to the next generation, number of wolves and … for different sections of the algorithms. To improve the effectiveness of ICA, trials and errors were made to obtain the best value for each parameter. These parameters are presented in Table 2.

Several input structures, including daily discharge and SSL of previous days were used and daily SSL values were predicted to evaluate the performance of the algorithm used to predict sediment load amounts.

Table 3. Parameters used in ICA

Value	Parameter
100	The number of initial countries
6	The number of initial colonists
100-6=94	The number of colonies
2	β
π/4	γ
0.01	ζ

2.4. Normalization of Data

Data normalization aims to unify the importance of different inputs in the used models. Since the input of raw data reduces the speed and accuracy of the model, inputs and outputs should be standardized between 0 and 1. Hence, the data used in the models were normalized by Eq. (5).

$$Z_n=\frac{Z-Z_{min}}{Z_{max}-Z_{min}} \tag{5}$$

Where Z represents the raw data, Z_n is the normalized data, Z_{min} is the minimum data, and Z_{max} is the maximum data.

2.5. Model Performance Criteria

Using the parameters of the correlation coefficient and root mean squared error according to Eq. (6)-(8), the capabilities of the suggested methods were evaluated. Correlation coefficient:

$$r=\frac{\sum_{i=1}^{n}(x_i-x)(Y_i-Y)}{\sum_{i=1}^{n}\sqrt{(x_i-x)^2}\sqrt{\sum_{i=1}^{n}(Y_i-Y)^2}} \tag{6}$$

Root mean square error:

$$MSE=\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-y_i)^2} \tag{7}$$

where X_i is the predicted values, Y_i is the observed values, X is the mean of x, and Y is the mean of Y.

2.6. Results and Discussion

In this research, the daily discharge and SSL of the years 2005-2015 were used as the input of ICA, and the values of daily suspended load were predicted by this algorithm. At first, all available data were examined with standard normal homogeneity test, which is one of the most commonly used methods to assess the homogeneity of the data (Table 4). After introducing the input structures and finding the optimal values of the effective parameters of the algorithm and applying them to the algorithm and also after training the extracted algorithm based on 70% of the data, in the next step, the developed algorithm was used for testing. In the test or validation section, the numbers obtained from ICA were compared with the observed suspended sediment values at the station based on the evaluation criteria.

Table 4. Evaluating the efficiency of the proposed algorithm in predicting suspended sediment load

The results of the training data from ICA		The results of test data from ICA	
RMSE (mg/L)	R^2	RMSE (mg/L)	R^2
235	0.85	242	0.89

According to Table 4, root mean square error (RMSE=235) and correlation coefficient (R^2=0.89), were obtained which represents the correct accuracy of ICA. The maximum predicted sediment and the total volume of SSL are compared by ICA with observed amounts in Tables 5 and 6. Since the estimation of the total volume of SSL has a determinant role in water resources management, the total volume of SSL is predicted by ICA (Table 6). According to the results presented in Table 6, it is evident that the sediment value predicted by ICA is 118723, which has an error of 10% versus the observed amount, indicating that the maximum predicted sediment amounts and the total volume of SSL by ICA are consistent with the observed values.

Given that ICA provides more optimal results, the results of this optimal algorithm are compared with the observed values in this section (Figure 2).

As can be seen from Figure 2, the results of estimating the sediment values by ICA is in a good agreement with the observed values, and it shows the acceptable efficiency and flexibility of ICA.

Table 5. Comparison of the maximum predicted sediment with observed values

Maximum sediment values <3000	The results of ICA (ton)	Relative error (%)
		ICA
7036	5180	26
6101	5760	5.6
4977	3751	24.6
4102	3871	5.7
3806	2520	33
3749	3114	16.9
3177	4012	26

Table 6. Comparison of the total suspended sediment load predicted by the ICA algorithm and the observed values

Observed amounts (ton)	The results of ICA (ton)	Relative error (%)
		ICA
104727	118723	22

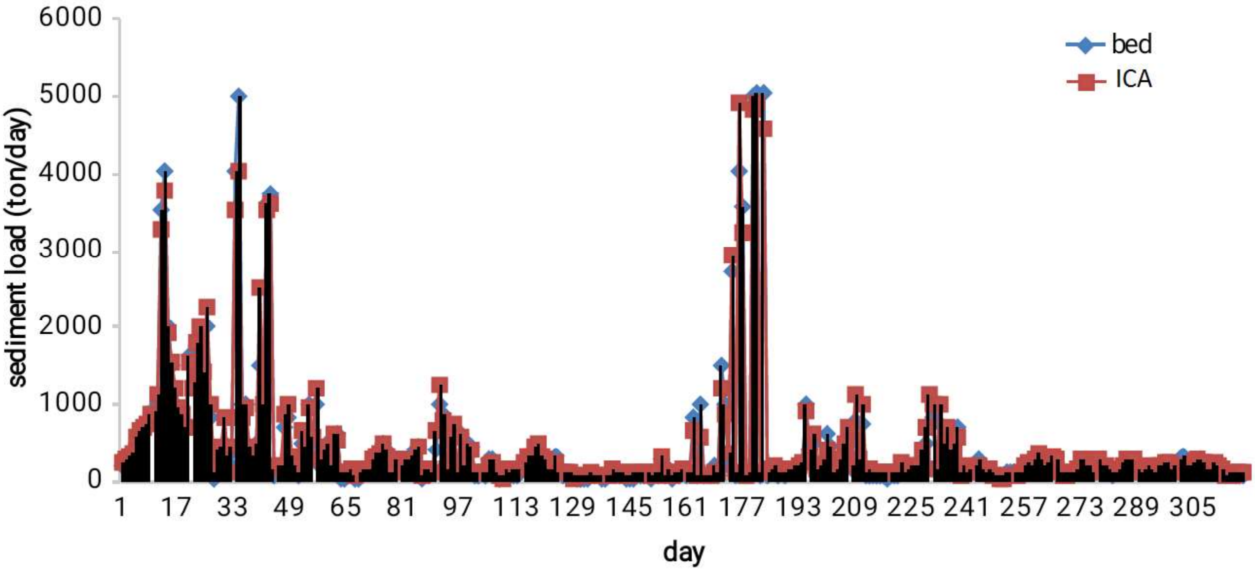

Fig. 2. Comparison of the observed and predicted values by the ICA algorithm

3. Conclusion

The main aim of the study was to evaluate the Imperialist Competitive algorithm (ICA) function to estimate the suspended sediment load of the Zarrinehrood river and compare its results with the observed data. The obtained results showed that ICA had higher accuracy to predict and estimate suspended sediment load versus the observed data. The results also indicated that ICA minimizes the objective function values to the optimal value. Therefore, it can be concluded that by choosing the discharge and suspended sediment load in the target day, the optimum result of ICA can be obtained in the study area.

4. References

1. zOZturk, F., Apaydin, H.,and Walling, D. (2001). "Suspended sediment loads through flood events for streams of Sakarya basin." Journal of Engineering Environment 25: 643-650.
2. Kalteh, A. M. (2008). "Rainfall-runoff modelling using artificial neural networks (ANNs): modeling and understanding." Caspian Journal of Environmental Sciences 6: 53-58.
3. Kuok, K., Harun, S., and Shamsuddin, S. (2010). Particle swarm optimization feed-forward neural network for modeling runoff. International Journal of Environmental Science & Technology, 7: 67-78.
4. Guo, W. and H. Wang (2010). "PSO optimizing neural network for the Yangtze river sediment entering estuary prediction." In 2010 6th International Conference on Natural Computation 4: 1769-1772.
5. Gholami, V., Darvari, Z., and Saravi, M (2015). Artificial neural network technique for rainfall temporal distribution simulation (Case study: Kechik region), Caspian Journal of Environmental Sciences, 13: 53-60.
6. Chen, X. Y. and K. W. Chau (2016). "A hybrid double feed-forward neural network for suspended sediment load estimation." Water Resources Management 30: 2179-2194.
7. Kisi, O., and Zounemat-Kermani, M., (2016), Suspended Sediment Modeling Using Neuro-Fuzzy Embedded Fuzzy c-Means Clustering Technique. Water Resources Management,30: 3979-3994.
8. Buyukyildiz, M., and Kumcu, SY. (2017), An Estimation of the Suspended Sediment Load Using Adaptive Network Based Fuzzy Inference System, Support Vector Machine and Artificial Neural Network Models. Water Resources Management, 31: 1343-1359.
9. Kisi, O. (2005). "Suspended sediment estimation using neuro-fuzzy and neural network approaches " Hydrological Sciences Journal 50(4): 683-696.
10. Altunkaynak, A. (2009). "Sediment load prediction by genetic algorithms " Journal of Advance Engineering Software 40: 928-934.
11. Mohammadrezapour, O., Nour jou, P., and Zeynali, MJ., (2015). "Genetic algorithm model for the relation between flow discharge and suspended sediment load (Gorgan River in Iran)." Electronic Journal of Geotechnical Engineering 16: 539-555.
12. Ebrahimi, H., Jabbari, E., and Ghasemi, M. (2013). Application of Honey-Bees Mating Optimization algorithm on Estimation of Suspended Sediment Concentration. World Appl Sci J, 22(11), 1630-1638.
13. Kisi, O. and J. Shiri (2012). "River suspended sediment estimation by climate variables implication: comparative study among soft computing techniques." Computer and Geosciences 43: 73-82.
14. Kakaei Lafdani, E. K., Nia, A. M., and Ahmadi, A. (2013). Daily suspended sediment load prediction

using artificial neural networks and support vector machines. Journal of Hydrology, 478, 50-62.
15. Ghorbani, M. A., Hosseini, S. H., Fazelifard, M. H., and Abbasi, H. (2013). Sediment load estimation by MLR, ANN, NF and sediment rating curve (SRC) in Rio Chama river. Journal of Civil Engineering and Urbanism, *3*(4), 136-141.
16. Heng, S., and Suetsugi, T. (2013). Using artificial neural network to estimate sediment load in ungauged catchments of the Tonle Sap River Basin, Cambodia. Journal of Water Resource and Protection, 5(02), 111.
17. Kumar Goyal, M. (2014). "Modeling of Sediment Yield Prediction Using M5 Model Tree Algorithm and Wavelet Regression." Journal of Water Resources Management 28: 1991-2003.
18. Seutloali, K. E., and Beckedahl, H. R. (2015). Understanding the factors influencing rill erosion on roadcuts in the south eastern region of South Africa. Solid Earth, 6(2), 633-641.
19. Liu, X., and Beljadid, A. (2017). A coupled numerical model for water flow, sediment transport and bed erosion. Computers & Fluids, 154, 273-284.
20. Ebtehaj, I., and Bonakdari, H. (2016). "Assessment of evolutionary algorithms in predicting non-deposition sediment transport." Urban Water Journal 13: 499-510.
21. Matos, J. P., et al. (2018). Probabilistic prediction and forecast of daily suspended sediment concentration on the Upper Yangtze River. Journal of Geophysical Research: Earth Surface, 123(8), 1982-2003.
22. Atashpaz-Gargari, E., & Lucas, C. (2007). Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition. In 2007 IEEE congress on evolutionary computation (pp. 4661-4667). IEEE.