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Assessment of GEP and ANN for Predicting Suspended Sediment Load: A Case Study of Ghatoor and Aland Rivers, West Azerbaijan, Iran

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Abstract

Estimation of the volume of suspended sediment load of rivers, especially when dam constructed on it, is one of the tremendous challenges that civil engineers faced. It is crucial to accurately predict the suspended sediment load to effectively mitigate the negative consequences of this phenomenon. To estimate the total suspended sediment accumulated behind the Aland and Ghatoor dams, two models of artificial intelligence, Gene Expression Programming (GEP) and Artificial Neural Network (ANN), were employed in this study. The performance of these two AI models compared with the traditional method, Sediment Rating Curve (SRC), for estimating the suspended sediment volume using hydrometric stations from 1969 to 2017. Unfortunately, the appropriate data from 2017 to the present is not available from authorities of the West Azerbaijan province, so inevitably, we used the hydrologic records till the end of the year 2017 in this article. Two statistical indices were used to evaluate the models: the coefficient of determination (R-squared) and the Mean Absolute Error (MAE). Based on these indices, the intelligent models performed better than the SRC in estimating the suspended sediment volume. In comparing the GEP and ANN models, the performance criteria show that the ANN model produces better results. For the Ghatoor River, the performance indicators of the ANN model were MAE=993.1 ton/day and R^2=0.910, which is 45% and 43% higher than the GEP model and SRC method, respectively. For Aland River, the performance indicators of the ANN model were MAE=519.2 ton/day and R^2=0.961, which is 12% and 57% higher than the GEP model and SRC method, respectively. In conclusion, for predicting the suspended sediment load in Ghatoor and Aland Rivers, the ANN model can be the best choice for this purpose.

1. Introduction

The accumulation of sediment is a major problem that can have detrimental impacts on the functioning of reservoir dams, pumping stations, and other hydraulic structures (Emamgholizadeh et al., 2018; Emamgholizadeh and Fathi-Moghdam, 2014; Fathi-Moghadam et al., 2010). Generally, the runoff from precipitation in every watershed conveys soil particles from

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the upper hand of the basin to the lower hand, the place that is the best choice for constructing a reservoir dam. The phenomenon of soil erosion is largely caused by deforestation, which also leads to sedimentation that negatively impacts water resource management (Khan et al., 2023), water quality and aquatic ecosystems (Allawi et al., 2023; Bilotta and Brazier, 2008; Khosravi et al., 2022), estimating suspended sediment is crucial. The engineers in this field must accurately estimate the total sediment volume with minimal error. There are several methods to estimate the suspended sediment load in rivers including empirical approaches like the Sediment Rating Curve (SRC) and intelligent models such as Artificial Neural Network (ANN), Gene Expression Programming (GEP), and Adaptive Neuro-Fuzzy Inference System (ANFIS) (Bazoobandi et al., 2022). Studies in the past have shown that intelligent models are more accurate in predicting variables for various problems such as soil sciences, river engineering, irrigation engineering, and etc (Emamgholizadeh et al., 2013, 2017a; 2018b; Gholipoor et al., 2012; Ghorbani et al., 2015; Kashi et al., 2014; Maroufpoor et al., 2018).The amount of suspended sediment load can be influenced by various hydrologic factors such as discharge rate, flow velocity, water depth, and also slope, cross-sectional area, temperature, and sediment properties (Emamgholizadeh and Karimi Demneh, 2019). However, Aytek and Kişi (2008) found that utilizing all of these parameters in the modeling process did not yield optimal or applicable results. The reason is when we have several factors interfering in the model; the network may be confused and it causes wrong predictions from the intelligent model. In this study, we assume that the sediment volume (Q_s) is just dependent on the flow discharge (Q_w).

Nowadays, the engineers prefer to use intelligent models to solve non-linear problems related to computing suspended sediment load, rather than relying on traditional methods and often inaccurate formulas. Kisi et al. (2012) proposed the GEP, Adaptive Neuro-Fuzzy Inference System (ANFIS), ANN, and Support Vector Machine (SVM) models to predict the daily suspended sediment load. Shamaei and Kaedi (2016) implied GP and neuro-fuzzy systems for estimating total suspended sediment. All the above-mentioned methods have some advantages and disadvantages in facing different problems; however, we are going to discuss and review particularly the GEP and ANN methods for the case study of Ghatoor and Aland Rivers. This study is centered around the estimation of the quantity of suspended sediment transported by the Ghatoor River in the Ghatoor basin and the Aland River in the Aland basin (as depicted in Figure 1) utilizing intelligent models. The main objective is to compare the performance of the GEP and ANN models in predicting sediment volume for these two rivers and compare the results with the traditional method of SRC.

In this research work, we assessed two AI models, and found out in which structure they are in their optimal condition. The engineers can use the introduced methods in other relevant projects to heighten the efficiency of the site work. Moreover, the old formulated methods had been put away; thus, time and calculation energy will be saved. As a result, for the case study of Ghatoor and Aland Rivers, by implying these presented AI models, the suspended sediment load carried by these rivers and accumulated beyond their dams could easily be estimated for any favored year in the future.

2. Materials and Methods

2.1. Studied area

The studied area is located in the West Azerbaijan province adjacent to Khoy City. Ghatoor and Aland are two sub-basins that are reviewed in this article (see Fig. 1). The geographical location of this area is between $36^0\,47'\,00''$ N to $38^0\,17'\,00''$ N and $44^0\,00'\,00''$ E to $44^0\,56'\,00''$ E. The Aland sub-basin is in the northern, and the Ghatoor sub-basin is in the southern part of this area. These two sub-basins have the flow direction of west to east, and are on the border with Iraq country from the west side.

The Ghatoor River is an important tributary of the Aras River, originating from the mountains of Turkey. The Ghatoor sub-basin has a catchment area of 110 km^2. There are various branches including Mash'yChay and Gharan connected to this river, while it flows in its path. It is important to note that the Ghatoor River receives its precipitation from rain and snow. The length of this river is 130 km. The place for constructing the Ghatoor dam is determined in $38^0\,15'\,00''$ N to $38^0\,45'\,00''$ N and $44^0\,15'\,00''$ E to $45^0\,00'\,00''$ E. The elevation of this sub-basin is between 1427 m to 3609 m above the sea level. Based on the data, the average yearly rainfall in this sub-basin was 369.6 mm. The highest and lowest yearly rainfall recorded were 684.2 mm and 165.4 mm, respectively. Table 1 shows additional physical characteristics of this sub-basin.

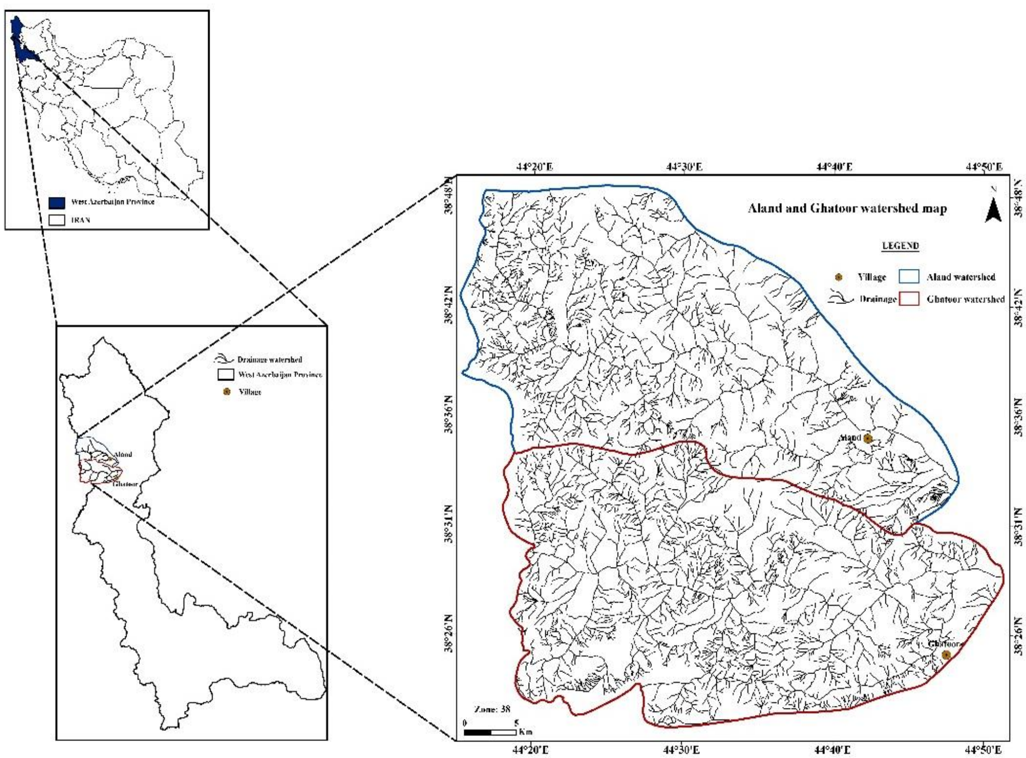

Figure 1. The Geographical map of the area of study in West Azerbaijan Province, Iran.

Aland River is one of the crucial branches of the Ghatoor River. This river originates from Kani-Ziarat, Nazar-Beig, and Haji-Beig mountains. The length of the Aland River is 100 km, and its catchment area is 1000 km^2. The Aland River and Ghatoor River both receive precipitation from rain and snow. The Aland River basin has an elevation ranging from 1582 m to 3332 m above the sea level. Based on the data, the sub-basin had an average annual precipitation of 489.7 mm. The maximum and minimum annual precipitation recorded were 906.5 mm and 219.1 mm, respectively. Table 1 provides additional physiographic characteristics of the basin.

Table 1. Physiographic characteristics of Ghatoor and Aland sub-basins.

Characteristic	**Unit**	**Sub-basin name**	
		Ghatoor	**Aland**
Basin area	Km^2	1473	599.9
Basin slops	m/m	0.0263	0.036
Basin lengths	Km	83.1	48.63
Perimeter	Km	218.9	132.3
Shape factor	Km^2/km^2	0.21	0.25
Mean basin elevation	m	2512	2458
Max flow distance	Km	118.53	64.87
Max stream length	Km	116.74	63.13

As long as sediment volume is straightly dependent on the flow discharge, and the flow discharge is related to the catchment area and precipitation, each of these two areas has a different quantity of suspended sediment accumulating behind the dams. In this paper, we use the data from two hydrometric stations, Pol-Yazdekan for the Ghatoor River and Badalan for the Aland River, containing daily flow discharge (Q_w) and sediment discharge (Q_s) for the GEP and ANN models. Table 2 contains the statistical indices for this dataset. The whole data set for Ghatoor and Aland area consists of 737 and 686 records, respectively, which it has been divided into a training set (70% of records) and a testing set (30% of records). The scatter plot shown in Figure 2 displays the correlation between flow discharge and sediment volume for both Ghatoor and Aland River.

Table 2. Statistical indices of gathered data for Ghatoor and Aland River.

Station	Q_w (m^3/s)				Q_s (ton/day)			
	Min	Mean	Max	Std. dev	Min	Mean	Max	Std. dev
Ghatoor	0.320	5.208	61.990	5.633	7.217	3163.870	108169.380	8965.634
Aland	0.042	3.465	36.710	4.616	0.356	1072.057	33350.246	3121.410

(a) (b)

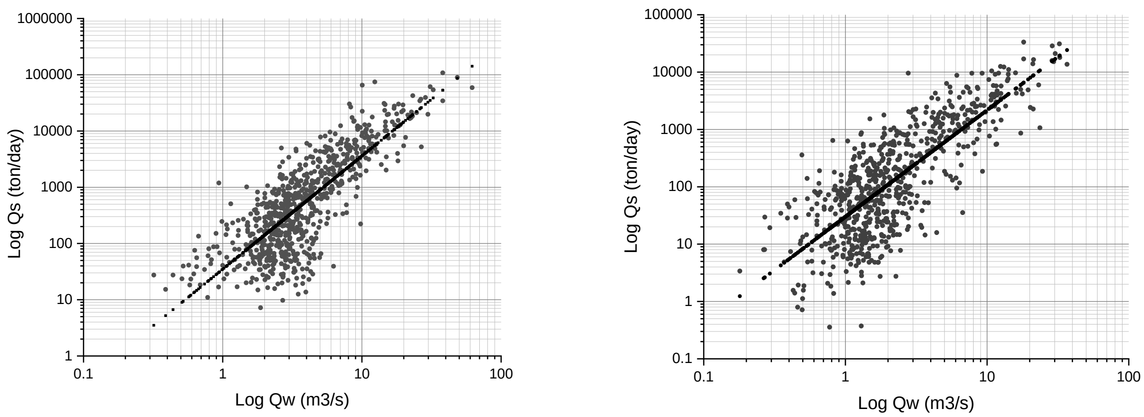

Figure 2. The scatter plot of Log Q_s and Log Q_w for (a) Ghatoor River and (b) Aland River.

2.2. Intelligent models

In this study, we utilized two intelligent models, GEP and ANN, to analyze the collected data. The GEP method was initially introduced by Candida Ferreira in 2006 (Ferreira, Gene expression programming: mathematical modeling by an artificial intelligence, 2006). This intelligent model works like a metaheuristic model GP that was first presented to the mathematical society by Koza and computing (1994). However, there are some basic differences in the individual's nature in these two methods. Ferreira (Automatically defined functions in gene expression programming 2006) asserts that in GP, individuals are non-linear entities of different sizes and shapes that are expressed as parse trees. On the other hand, in the GEP, individuals are encoded as linear strings of fixed length, which are expressed as non-linear entities of different sizes, and shapes, expression trees. To start the GEP model, we should define a random population of initial chromosomes. Then the desirability of these initial chromosomes is assessed by a fitness function. Several fitness functions could be used in the GEP model including Root Relative Square Error (RRSE), Mean Square Error (MSE), Mean Absolute Error (MAE), etc. In this case, we consider RRSE as a fitness function for developing our GEP model.

ANN is an intelligent model first introduced in 1943 by neurophysiologist Warren McCulloch and mathematician Walter Pitts (McCulloch and Pitts, 1943). Artificial Neural Networks are inspired by human brain operation. ANN can be used for modeling and approximation of functions, classifying, clustering, prediction and estimation, pattern detection, signal processing, system identification, and control (Fausett, 2006). We use ANN for the purpose of modeling and data estimation and prediction. Generally, in supervised learning problems, networks like Multi-Layer Feed Forward (MLFF), Multi-Layer Perception (MLP), Radial Basis Function (RBF) or Support Vector Machine (SVM) are suitable. Regular artificial neural networks are consisting of one or several layer(s), and each layer carries several little components connected to each other, named neurons (Nagy et al., 2002). In this project, we imply most of the above-mentioned methods for training the network and the presented best result of them. Moreover, the Back Propagation (BP) structure is used for shaping the network.

For evaluating the model's performance and suitability, we have two parameters, MAE and R^2. The mathematical formula for these two values is presented in Eq. 1. and Eq. 2:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|O_i - P_i| \quad (1)$$

$$R^2 = \frac{\sum_{i=1}^{N}(O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^{N}(O_i - \bar{O})^2 \sum_{i=1}^{N}(P_i - \bar{P})^2}} \quad (2)$$

where N is the number of data records, O_i is the quantity of observed data, P_i is the quantity of predicted data, and $\bar{O}$ and $\bar{P}$ is the mean of observed data and predicted data, respectively.

2.3. Model initialization

It is necessary to find the best input combinations to have the greatest performance for our model. For determining the best combination of inputs, methods such as trial and error and correlation analysis are used. The trial-and-error method is time-consuming, and the correlation analysis does not exactly determine the lag values. For these reasons, we use three statistical parameters to check the best lag values of inputs.

The first is the Auto-Correlation Function (ACF), which is a statistical representation used to analyze the degree of similarity between a time series and a lagged version of itself. ACF helps the analyst to compare the current value of a dataset to its past value. The second is the Partial Auto-Correlation Function (PACF), which is a summary of the relationship between an observation in a time series with observations at prior time steps with the relationships of intervening observations removed. The last parameter is the Cross-Correlation Function (CCF), which is a measurement that tracks the movements of two or more sets of time series data relative to one another (Salas, 1980; Senthil Kumar et al., 2012).

In this study, we draw ACF and PACF graphs for the output of the model, sediment volume, to determine the meaningful lag values for this variable in the Ghatoor and Aland datasets in its time series (see Figs. 3(a), 3(b), 3(d), and 3(e)). Furthermore, the CCF graph between our two variables, flow discharge and sediment volume are shown in Fig. 3(c) and 3(f). These graphs are exported from MATLAB R2020b. By analyzing these graphs, we can choose the best selection of inputs for our intelligent models. As is shown for Ghatoor dataset, in ACF and PACF graphs (Fig 3(a) and 3(b)), the autocorrelation and partial autocorrelation coefficient exceeded the confidence boundary in lag days 1, 15, and 16. Also in Fig 3(c), the cross-correlation value between Q_s and Q_w exceeded from confidence boundary in lag days 2 and 3, as well as 1, 15, and 16.

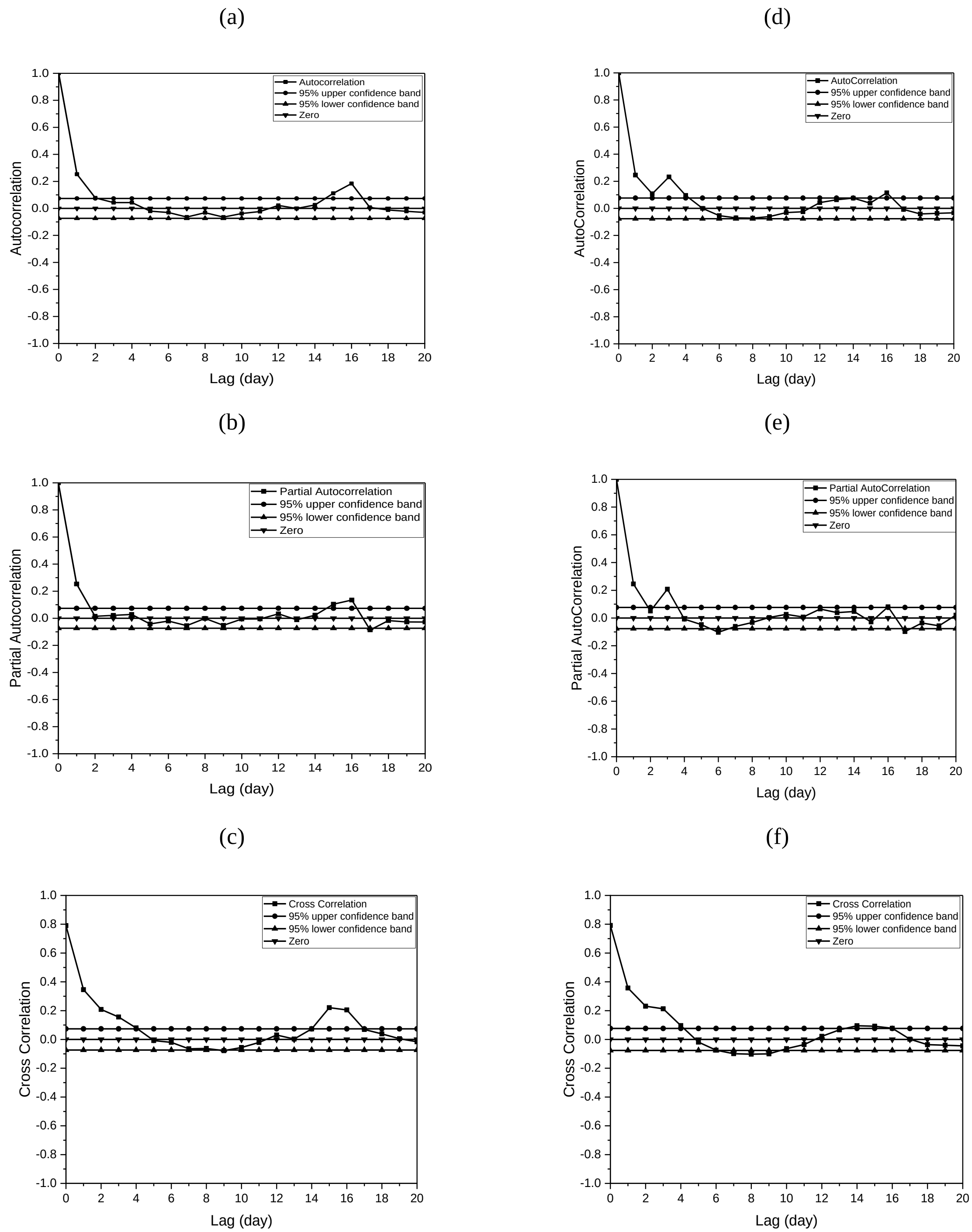

Figure. 3. (a), (b), and (c) are autocorrelation, partial autocorrelation for sediment volume, and cross-correlation between flow discharge and sediment volume for Ghatoor River, respectively. (d), (e) and (f) are autocorrelation, partial autocorrelation for sediment volume, and cross-correlation between flow discharge and sediment volume for Aland River, respectively.

By assessing Aland dataset, in ACF and PACF graphs, Figs. 3(d) and 3(e), the autocorrelation and partial autocorrelation coefficient exceeded the confidence boundary in lag days 1, 3, and 16. However, we can waive the effect of lag day 16 in this case because of its little difference with the confidence line. In addition, in Fig. 3(f) the CCF values in lag days 1, 2, and 3 are considered for this dataset. However, in this time series, it is preferred to not consider lag times that are greater than 3 days, because it makes our intelligent model confused. Finally, the input combination for Ghatoor and Aland rivers can be defined as Eq. 3 and Eq. 4, respectively:

$$Q_s = f(Q_w, Q_{w-1}, Q_{w-2}, Q_{w-3},, Q_{s-1}) \quad (3)$$

$$Q_s = f(Q_w, Q_{w-1}, Q_{w-2}, Q_{w-3}, Q_{s-1}, Q_{s-3}) \quad (4)$$

2.4. GEP model

According to Ferreira (Gene expression programming: mathematical modeling by an artificial intelligence 2006), for developing the GEP model, finding the best fitness function is necessary. For this purpose, Eq. (6) was chosen for being a fitness function in our intelligent model (Emamgholizadeh and Karimi Demneh, 2019; Emamgolizadeh et al., 2015a; Parhizkar et al., 2015). In order to acquire Eq. (6), the quantity of the Root Relative Square Error (RRSE), calculated from Eq. (5):

$$RRSE_i = \sqrt{\frac{\sum_{j=1}^{N}(P_{ij} - T_j)^2}{\sum_{j=1}^{N}(T_i - \bar{T})^2}} \quad (5)$$

$$f_i = 1000 \times \frac{1}{1 + RRSE_i} \quad (6)$$

where P_{ij} is the predicted value by the i^{th} individual chromosome, and T_j is a target value for assessing the fitness of the model. Also the bar shows the mean value of its parameter (Ferreira, Gene expression programming: mathematical modeling by an artificial intelligence, 2006).

To continue the model, a set of terminals has been selected for generating genes; terminal sets are defined as time-lagged flow discharge and sediment volume. Other parameters should have been defined for evolving the model including number of genes, gene’s head size, number of chromosomes, linking function, and selection of genetic operators and their weight. Each of these parameters has to be in their optimized quantity to have an accurate model. Based on achievements in (Ferreira, Gene expression programming: mathematical modeling by an artificial intelligence, 2006), the best value for the number of genes is 1 to 3. In addition, the number of chromosomes for the quantity of 30 and the head size of 8 for Ghatoor River and 7 for Aland River resulted in better answers for our GEP model. Due to other researchers’ conclusions in their past studies, the addition function is regularly better option for using it as a linking function (Emamgolizadeh et al., 2015b; Kisi et al., 2012). There are more parameters of the GEP model and their quantity presented in Table 3.

Table 3. Parameters of GEP model.

Number	Parameter's name	Setting and Quantities
1	Number of genes	4 (for Ghatoor) & 3 (for Aland)
2	Number of chromosomes	30
3	Head size	8 (for Ghatoor) & 7 (for Aland)
4	Genetic operators	$+,\times,-,\div, power, \sin x, \cos x, exp, arc\ Tan\ x, x^2, x^3, ln, \sqrt[3]{}, \sqrt{},$
5	Mutation rate	0.044
6	Inversion rate	0.1
7	IS rate	0.1
8	RIS rate	0.1
9	Gene transportation rate	0.1
10	One point recombination rate	0.3
11	Two-point recombination rate	0.3
12	Gene recombination rate	0.1

In Figure 4, the Expression Trees (ETs) for both the Ghatoor and Aland River GEP models are depicted. These trees demonstrate the correlation and mathematical connection between each gene, and how the model produces results and computes answers.

For Ghatoor River, the equation 7 formulas were extracted from the GEP model. For Aland River, the equation 8 were extracted from the GEP model: These mathematical formulas can be applied to calculate flow discharge and sediment volume within the limits specified in Table 2.

$$\begin{aligned} Q_s &= G_{1-Ghatoor} + G_{2-Ghatoor} + G_{3-Ghatoor} + G_{4-Ghatoor} \\ G_{1-Ghatoor} &= Cos(Q_{w-2} - Q_w) \times [19.495Q_w - Q_w^2] \\ G_{2-Ghatoor} &= (Q_w - Q_{w-3})^2 \times (9.219 + Q_{w-1}) \\ &\quad \times Sin(Q_{w-2}^2) \\ G_{3-Ghatoor} &= ((16.117 - Q_{w-1}) + (6.7 \times Q_w))^2 \\ &\quad - \log(Q_{w-3}) \\ G_{4-Ghatoor} &= \left(\frac{Q_w \times Q_{w-2}}{Q_{w-3} - 8.149}\right) + \left(\frac{8.149 \times Q_w}{Q_{w-1}}\right) \end{aligned} \tag{7}$$

$$\begin{aligned} Q_s &= G_{1-Aland} + G_{2-Aland} + G_{3-Aland} \\ G_{1-Aland} &= (-6.714 + \cos(Q_{s-3})) \times (Q_{w-2}^2 \times \cos(Q_{w-1})) \\ G_{2-Aland} &= (Q_{w-3} - (2.401^2 \times Q_{w-2}) - Q_{w-3})^2 \\ G_{3-Aland} &= (\sqrt{Q_{w-2}} \times Q_{s-3})^2 + (\sqrt{Q_w} \times \exp(1.834)) \end{aligned} \tag{8}$$

Table 4. GEP model ultimate results.

River	Training		Testing		Fitness function training	Fitness function testing
	R^2	MAE (ton/day)	R^2	MAE (ton/day)		
Ghatoor	0.749	1862	0.745	1655	666.5	655.5
Aland	0.842	529.0	0.453	751.7	715.2	543.9

2.5. ANN model

When creating an artificial neural network, there are various parameters that can impact its performance. These include the number of hidden layers, the number of neurons in each layer, the type of transfer function used to connect the neurons, and the training method employed (Emamgholizadeh, 2012; Emamgholizadeh et al., 2017; Gholipoor et al., 2012). The ANN models for Ghatoor and Aland River have different network structures. The Ghatoor model has one hidden layer with 10 neurons, while the Aland model has one hidden layer with 6 neurons. Moreover, the training algorithm of Bayesian Regularization and back-propagation method for training the network was used for both models. After analyzing the outcomes obtained from various network structures, we can deduce that the networks with the characteristics mentioned above exhibit superior efficiency with higher R^2 values. Our study employs MATLAB R2020b to simulate the neural networks. In Fig. 5, we display two diagrams that compare the results obtained from different network training approaches for Ghatoor and Aland River. Furthermore, Table 5 includes the final outcomes for the most effective ANN model.

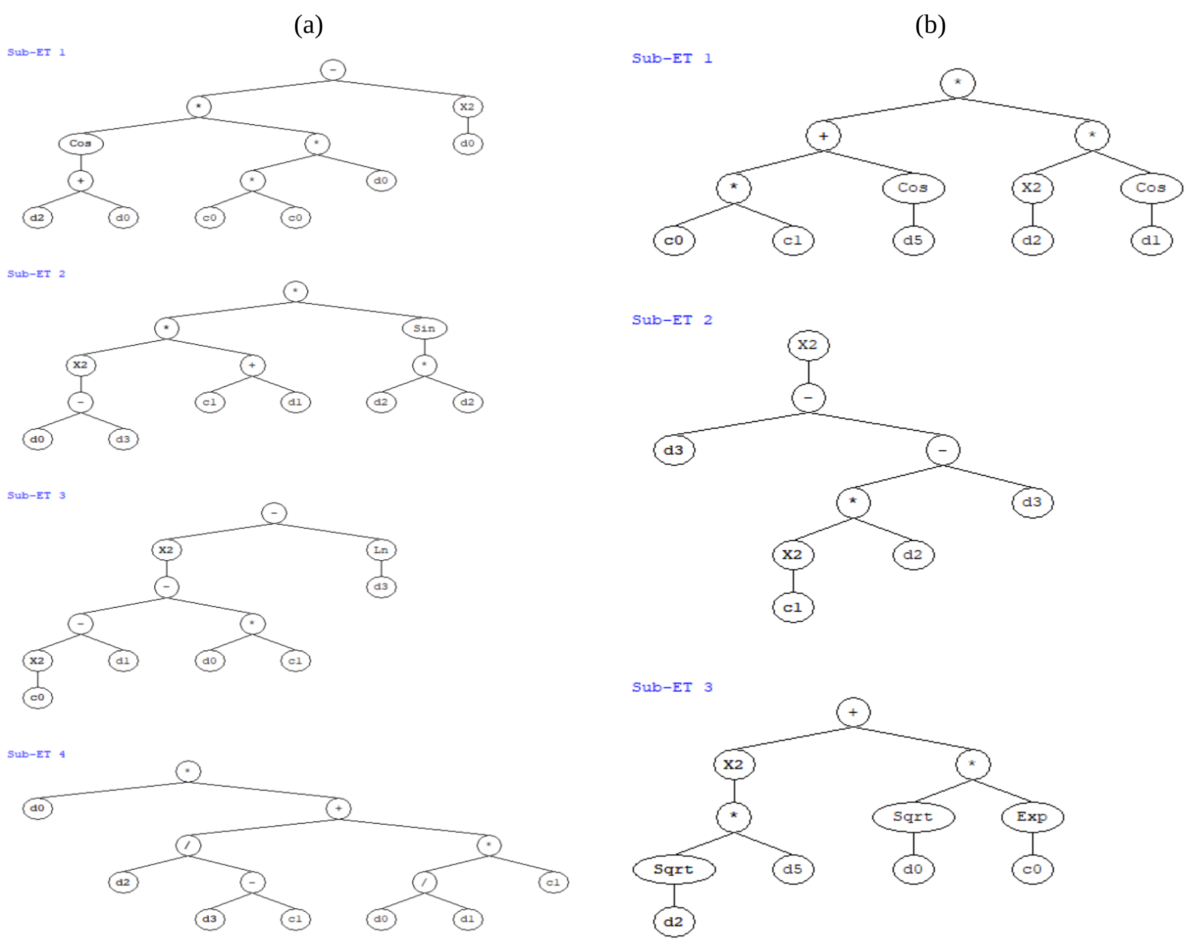

Figure 3. Expression trees extracted from GEP model for (a) Ghatoor River and (b) Aland River.

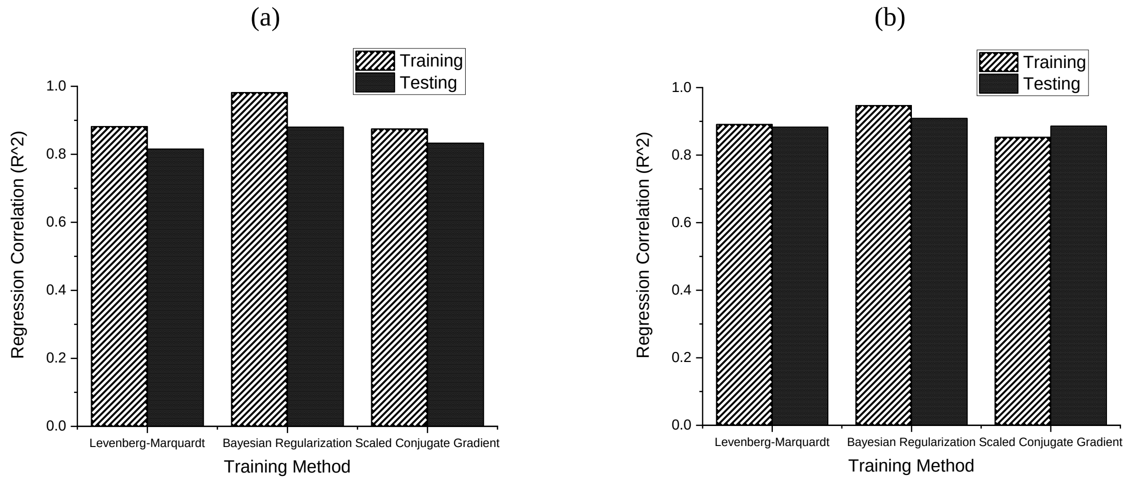

Figure 5. Regression correlation *vs.* different training methods for (a) Ghatoor River and (b) Aland River.

Table 5. Results for best ANN model.

River	R^2 training	MAE (ton/day)	R^2 testing	MAE (ton/day)
Ghatoor	0.910	993.1	0.860	1012.6
Aland	0.947	529.3	0.909	580.7

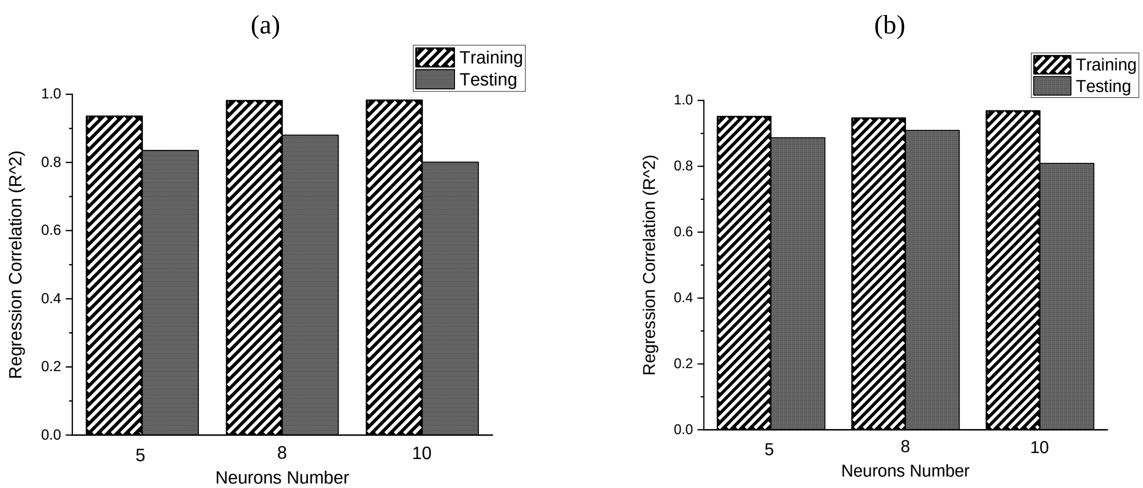

Figure. 6. Regression correlation *vs.* neuron numbers in the hidden layer, with Bayesian regularization training method, for (a) Ghatoor River and (b) Aland River.

2.6. Sediment rating curve (SRC) method

Prior to the creation of intelligent models, hydraulic engineers relied on empirical relationships to determine the amount of suspended sediment load present in watersheds by analyzing the flow discharge. In the late 20th and early 21st century, the researchers introduced an empirical method called the Sediment Rating Curve (SRC) method. This method, introduced by Horowitz (2003); Jansson (1996); Syvitski et al. (2000), is widely used. The SRC is a power function, and Zhang et al. (2012) presented it in Eq. (9).

$$Q_s = aQ_w^b \tag{9}$$

In Eq. (9), 'a' and 'b' constants are determined by linear regression from graph log Q_s – log Q_w from the initial data gathered for analyzing (Fig. 2). According to linear regression analysis of scatter plots in Fig. 2, using Excel, values of 'a' and 'b' had been specified and the Eq. (9) turns into Eqs. (10) and (11) for Ghatoor and Aland River, respectively.

$$Q_s = 34.821\ Q_w^{2.0132} \tag{10}$$

$$Q_s = 29.964\ Q_w^{1.8582} \tag{11}$$

3. Results and Discussion

3.1. Comparing results of AI models to the SRC method

In this study, we are going to compare the results of the SRC method with intelligent models results, and then conclude which method is more efficient and applicable. In Table 5, we can review the evaluation parameters for each model to assess their performance. Table 5 indicates that the SRC method is less precise compared to the other two methods due to its lower coefficient of determination (R^2) and higher Mean Absolute Error (MAE) when compared to the two intelligent models. Table 5 indicates that the SRC method is less precise compared to the other two methods due to its lower coefficient of determination (R^2) and higher Mean Absolute Error (MAE) when compared to the two intelligent models. Consequently, the results from two intelligent models are more reliable than the SRC method for predicting sediment volume. By utilizing modern techniques such as intelligent models, we can achieve superior and more effective solutions for these types of issues.

Table 5. Comparison between the results of GEP and ANN, and SRC models for Ghatoor and Aland Rivers.

Model	River name			
	Ghatoor		Aland	
	R^2	MAE (ton/day)	R^2	MAE (ton/day)
GEP	0.749	1,862	0.842	529.0
ANN	0.910	993.1	0.961	519.2
SRC	0.634	1,820	0.603	659.6

According to Table 5, the intelligent models described in this paper are better at predicting the amount of suspended sediment in the Ghatoor River compared to the SRC method. Furthermore, the ANN model showed superior performance compared to the GEP model. The value of R^2 for the ANN model was 0.982, which is higher than the other two methods, and the MAE parameter is lower than the GEP and SRC methods; it shows that the average error in the prediction of the ANN model is the minimum in these three methods, and as a result, the ANN is more accurate. The accuracy of the models at the testing dataset has decreased, but there are reasons why this may not be significant. These reasons will be explained in the following paragraphs. In the Aland River dataset, intelligent models performed better than the SRC model, as well as Ghatoor River (see Table 5). Also, the ANN models had better results in comparison to the GEP model, due to the high R^2 and low MAE, which indicates the less error in the ANN model outputs and targets. By utilizing an introduced ANN model, we can obtain a more accurate estimation of the total suspended sediment volume for the Aland River. As it was mentioned in the previous paragraph, the accuracy in the testing dataset is lower than the dataset used for training the model.

The amount of MAE shows the mean absolute error between the outputs of the model and the target in the collected data from hydrometric stations. Although MAE is a considerable amount in each method of estimation, in facing these kinds of problems, this amount is acceptable for hydraulic engineers. The reason is that there are several parameters and uncertainties that interfere with sediment volume, but we just imply the precipitation records in our calculations and disregard other parameters in modeling and estimation. Therefore, it is inevitable to have a considerable amount of error in our modeling.

3.2. Comparing results of this study with latest related articles

In this section, we are going to compare the performance and results of these two AI models presented in this research work with the latest and other articles that published in the specific field of suspended sediment load estimation using AI models. In a recent published study, to assess soft computing techniques for predicting suspended sediment load, several methods have been used and compared with the conventional method SRC. The coefficient of determination of ANN model for two stations were 0.92 and 0.86, and this statistical parameter were 0.59 and 0.67 using conventional formulated SRC method, respectively (Khan et al., 2021). Additionally, Alijanpour Shalmani et al. (2022) concluded that AI models have shown great performance in predicting suspended sediment load with the coefficient of determination 0.92 for the ANN model and 0.88 for the GEP model. Lastly, in another research work, carried out for a region located in the United States, the results was the same of others, and intelligent models shown betters results that SRC method (Olyaie et al., 2015). Considering two hydrometric stations, the coefficient of determinations was 0.65 and 0.76 for the ANN models, 0.481 and 0.39 for the SRC method, respectively. Totally, in all of the related articles, the performance of AI models in estimation of suspended sediment load were higher, thus preferred to conventional methods like as SRC.

3.3. Sensitivity analysis

The primary goal of conducting sensitivity tests is to assess the impact of individual input parameters on the modeling process and resulting outputs. In this section, we conducted tests on the most effective intelligent model, the ANN, and the findings are detailed in Table 6. For each test, we removed a single input parameter and compared the performance criteria to the best ANN model (also outlined in Table 6). According to Table 6, for Ghatoor River, when Q_w has been removed from the dataset, we have the lowest coefficient of determination, 0.82, and the largest MAE, 1091 ton/day, in the results. It can be inferred that Q_w highly affected the accuracy of the model. As it is obvious, R^2 declined approximately, 16%, and MAE raised about 10% compared to the best ANN model. On the other hand, parameters like Q_w and Q_{s-1} have the lowest impact on the modeling process, and somehow it makes no difference to consider them as input parameters for the model or not. Same for Aland River, when Q_w has eliminated from the inputs of the model, the performance of the model sharply decreased, R^2 decreased by 31%, and MAE increased by 112%, which makes the results unreliable. Moreover, Q_{w-1} and Q_{w-2} have little effect on the model's performance; consequently, these parameters are not as important as Q_w in the suitability of the ANN model.

Table 6. Results of the sensitivity analysis and its comparison with the best ANN model.

Test	Ghatoor		Test	Aland	
	R^2	MAE (ton/day)		R^2	MAE (ton/day)
Best ANN	0.910	993.1	Best ANN	0.961	519.2
Best ANN without Q_w	0.82	1091	Best ANN without Q_w	0.66	1105
Best ANN without Q_{w-1}	0.87	1003	Best ANN without Q_{w-1}	0.92	581
Best ANN without Q_{w-2}	0.86	995	Best ANN without Q_{w-2}	0.93	533
Best ANN without Q_{s-1}	0.86	997	Best ANN without Q_{s-1}	0.89	603
			Best ANN without Q_{s-3}	0.91	588

4. Conclusion

In this research work, the GEP and ANN models were implied to estimate the sediment volume for the Ghatoor and Aland Rivers located in the northwest of Iran. The time-lagged daily flow discharge and sediment discharge are used as parameters for modeling in order to increase the model's accuracy. Moreover, according to statistical indices, the ANN model exhibited superior performance compared to the GEP model. For the Ghatoor River, the MAE of the estimated sediment volume by GEP was 1862 tons/day, and in the ANN model, was 993.1 tons/day. The coefficient of determination (R^2) was 0.749 for GEP and 0.910 for the ANN model. For the Aland River, the MAE of the estimated sediment volume by GEP was 529 tons per day and in the ANN, model was 519.2 tons per day. The coefficient of determination (R^2) was 0.842 for GEP and 0.961 for the ANN model.

In general, the results of this study illustrated that intelligent models are reliable ways to estimate the amount of suspended sediment load in rivers and are preferred to the traditional empirical methods like the SRC. After implementing the ANN, the mean absolute error (MAE) reduced by 47% and 45% for the Ghatoor River and by 2% and 21% for the Aland River, respectively, as compared to using the GEP and SRC methods. In conclusion, using intelligent models for solving problems like suspended sediment load can be preferred to traditional methods like empirical formulas.

Data Availability

The data used to support the findings of this study is available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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