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# Application of Whale Optimization Algorithm Combined with Adaptive Neuro-Fuzzy Inference System for Estimating Suspended Sediment Load

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## ABSTRACT

In Iran, no detailed information on the amount of erosion, sediment transport, and sedimentation of rivers, and in many cases, there are many differences between measurements. Since the flow regime and consequently the sediment regime in the drainage basins are not constant, estimation of sediment discharge can help estimate the sediment accumulated behind the water structures, especially the dams, and determining the dead volume of reservoirs in the coming months, and by adopting timely arrangements, the management of discharge will be facilitated to a certain extent during sedimentation. In this study, a hybrid method of the Whale optimization algorithm and the neuro-fuzzy inference system was used to estimate the suspended sediment load (*SLL*) of the Zarinehrood river. The performance of the proposed methods was evaluated by two statistics, including determination coefficient ($R^2$) and normal root mean square error (NRMSE). *SSL* of the Zarinehrood river during 10 years with flow discharge was used as inputs. The results showed the high accuracy of the WOA-ANFIS with values $R^2$=0.962 and NRMSE=0.051. In general, a comparison of the results obtained from the hybrid method used in this study showed the high ability and accuracy of the WOA-ANFIS method in estimating the *SLL* of the Zarinhrood river.

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## 1. Introduction

In river engineering designs, estimating the sediment load of the river is of great importance. The rivers of our country carry high sediment compared with the rivers of other regions of the world. This indicates the severity of erosion and the inappropriate state of natural resources. The high sediment rate, in addition to leading us to think about solutions to reduce erosion, also requires an understanding of the sedimentation status of the area and the accurate estimation of the amount of sediment output. 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. Any increase or decrease in the sediment load of the rivers results in various consequences such as the occurrence of degradation or aggradation phenomena, the change in the granularity of the material, and the shape of the plate and its longitudinal profile. To manage the erosion and sedimentation and 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, in terms of estimating the level of erosion and sediment of the drainage basin, estimating the useful life of dams, modifying sediment load sampling methods, and estimating sediment content in water, measuring sediment load of rivers is important [1]. A review of studies suggests that, before 1930, the main attention in the field of sediment was to provide equations for determining bed load. The determination of the suspended load and the presentation of its computational relations back to the 1930s and 1940s. The decade of the 1880s can be considered a major milestone in the study of river sedimentation. During this period, computers entered the field of study and, consequently, the rapid development of computer models, the study of the transfer process, and the determination of transferred sediment amount accelerated. Suspended sediment load is determined through direct measurements or sediment transport equations [2].

Limitations in equipment, time, and cost have posed challenges to laboratory study. Also, since the exact solution method (analytical solution) is unable to analyze models that have complex geometry and only numerical solution methods are effective in this field. Nowadays, with the development of software facilities and the use of new technologies, field measurements, precise laboratory experiments, and rapid processing of information, a better understanding of the sediment transfer process is provided. The process of obtaining a relationship to estimate the amount of sediment is a nonlinear mapping problem and new methods (optimization algorithms, artificial neural networks) are considered a powerful tool for solving such problems. The meta-heuristic algorithms are a set of algorithms for solving complex optimization problems, which are moving randomly but purposefully and simply in the solution space of the problem in search of the absolute optimal response. Several studies have been carried out on estimating and optimizing river sediment using methods such as genetic meta-heuristic algorithms, PSO, and various types of neural networks, which are referred to hereafter.

Recent studies in this field include studies, Kalteh et al. [3], Kuok et al. [2], Harun et al. [3], Guo and Wang [4], Gholami, Darvari et al. [5], Chen and Chau [6], Kisi and Zounemat-Kermani [7], Buyukyildiz and Kumcu [8], that using artificial neural networks, genetic programming, and optimization algorithms have estimated and estimated the suspended sediment of the river.

Mohammad Reza pour et al. [9] used a genetic algorithm to optimize the relationship between flow and sediment discharge for Nodeh station located on Gorganrood river. Then the results were compared by using the sediment rating curve (SRC). The evaluation of the results showed that the genetic algorithm had a higher accuracy than the SRC. Tabatabaei and Salehpour Jam [10] optimized the sediment rating curve coefficients of Gilan Shalmanrood river using daily flow discharge and suspended sediment discharge data using Genetic Evolutionary Algorithms (GA), Particle swarm optimization (PSO), non-monitored Artificial Neural Networks, and an ordinary regression model. The results showed that evolutionary algorithms are a suitable method for optimizing the sediment rating curve coefficients compared to non-monitoring artificial neural networks and ordinary regression models. Ebtehaj and Bonakdari [11] estimated river sediment using Imperialist Competitive (ICA) and particle swarm optimization (PSO) algorithms. The results showed that the ICA algorithm was superior to the PSO algorithm in sediment estimation. Muhammad Adhan [12] proposed a dynamic evolving neural fuzzy inference system (DENFIS) to estimate the suspended. The results showed that the DENFIS-based models improved the accuracy of the ANFIS-FCM and MARS-based models concerning RMSE by 33% (32%) and 31% (36%) for the Guangyuan (Beibei) station, respectively. Sadeghifar and Barati [12] used the adaptive neuro-fuzzy inference system (ANFIS) for estimation of the longshore sediment transport rate in the southern shorelines of the Caspian Sea. The trained ANFIS model outperformed the existing regression-type empirical equations for the estimation of the alongshore sediment transport rate due to the adaptive structure of the ANFIS model to better fit complex systems. Ebtehaj and Bonakdari [13] presented gene-expression programming to predicts sediment transport in the sewer. The results indicate the GEP model presents the results RMSE=0.12 and MAPE=2.56 for train and RMSE=0.14 and MAPE=2.82 for verification. Rezaie-Balf et al. [14] simulated physical and chemical parameters to efficiently improve the prediction of water quality index using the Kalman model of ANN. The results showed that Kalman model can evaluate the water quality of rivers more efficiently. Tabari et al. [15] developed a multi-objective model for Amir Kabir dam reservoir using non-dominated sorting genetic algorithm (NSGA-II) and dynamic artificial neural network (DANN) models. The results showed high efficiency of the used methods in allocation to the downstream water demands. Naderpour et al. [16] used artificial neural networks to predict the torsional strength of reinforced concrete beams strengthened with FRP sheets. The results showed that the idealized neural network predicted the torsional strength of RC beams with a high degree of accuracy. Ghanizadeh et al. [17] used the gaussian process regression (GPR) for estimating of resilient modulus of stabilized base materials. The results showed high accuracy of GPR method with regression coefficient of 0.997 and 0.986. Kumar et al. [18] presented a detailed analysis of optimization of a simple steel truss with discrete design variables using different variations of genetic algorithm. Darabi et al. [19] used three soft computing models, multilayer perceptron (MLP), ANFIS, and radial basis function neural network (RBFNN) to predict daily SSL. The results show that the ANFIS model had a better performance with RMSE=0.15-0.21 compared with other models.

Most previous studies have investigated the application of artificial neural networks (ANNs), regression models, and empirical equations in this field and limited research has been done on the use of new methods such as meta-heuristic algorithms. Due to the optimal efficiency of meta-heuristic algorithms with less cost and time to achieve an optimal response, the present study evaluates a combined method based on Whale optimization algorithm and neural-fuzzy inference system for estimating the suspended sediment load (*SLL*) of the Zarinehrood river in the southeast of Urmia lake. Given the successful applications of the WOA algorithm in engineering, as well as the fact that all of these methods are meta-heuristic methods that are inspired by nature and the strategy of each in achieving the optimal solution or the objective function is different. Therefore, in this study, to evaluate the performance and efficiency of WOA algorithm (for the first time) as a new evolutionary method and also the compatibility of this algorithm with fewer parameters was used to optimize *SLL*. Finally, the results of this study have been compared with other researchers' studies.

## 2. Methods

### 2.1. Case Study

Zarinehrood is a river in Kurdistan province and West Azarbaijan province, Iran. Its real name is Jegatoo, a well-known name among local residences over centuries. This basin between the longitudes of 45° 45' to 47° 15' E. and the latitudes of 35° 30' to 36° 45' N. The area of the Zarinehrood basin is about 13890 km$^2$. Zarinehrood reservoir dam is located on the Zarinehrood river in Kurdistan province, 85 km southwest of Miandoab city and east of Boukan city. The annual average rainfall and temperature in the Zarinehrood river basin are 527 mm and -1.8 ° C, varying from -26.5 ° C in February to 5 in August. In Figure 1, the position of the Zearinehrood River is shown on the map.

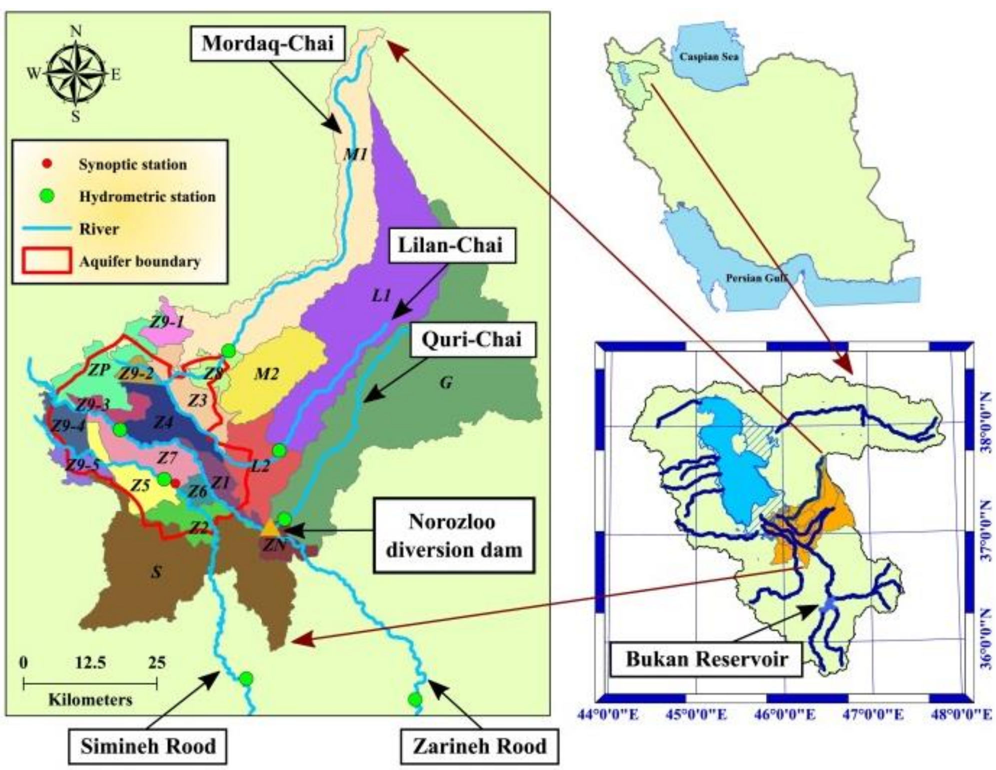


**Fig. 1.** Location of the Zarinehrood on the map.

To calculate the sediment discharge by each of the models, firstly, the required statistics and data such as daily discharge and suspended sediment load from 2005 to 2015 were used as inputs, and by that, the suspended load's daily values were estimated (Table 1).

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

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

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 assuming Zero assumption | Confidence level (a) | P-Value |
|---|---|---|---|
| Flow discharge | 60.4 | 0.05 | 0.58 |
| Sedimentdischarge | 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 zero and otherwise the assumption 1 is acceptable. According to the results of Table 2, precipitation data, sediment discharge, and flow discharge at the studied station (Sarighamish station on Zarinehrood river) are homogeneous and can be used safely. After ensuring homogeneity, two-thirds of the data (70% of the data) were used to train the models, and one-third of the remaining (30%) to test the obtained parameters using the WOA-ANFIS method.

## 2.2. Whale optimization algorithm (WOA)

The whale optimization algorithm (WOA) is a new meta-heuristic algorithm that mimics the Humpback hunting behavior. The main difference between this algorithm and other algorithms is the simulation of random hunting behavior or the best search factor for hunting pursuits. This algorithm starts with a set of random response. At each stage, the search agents update their position according to the random selection of the search agent or the best previously obtained response [20]. The mathematical model of the whale algorithm is as follows:

## 2.3. Encircling prey

Humpback whales can detect prey and surround them. The WOA algorithm assumes that the candidate for the best solution is currently the target prey. This behavior is shown by Equations 1 and 2:

$$\vec{D} = \left| \vec{C}.\vec{X}^*(t) - \vec{X}(t) \right| \tag{1}$$

$$\vec{X}(t+1) = \vec{X}^*(t) - \vec{A}.\vec{D} \tag{2}$$

In these relations, *t* is the current iteration, $\vec{A}$ and $\vec{C}$ the coefficient vector, $\vec{X}^*$ is the vector of the best solution ever obtained, and $\vec{X}$ the position vector of the object. Vectors A and C are calculated in the form of relations 3 and 4.

$$\vec{A} = 2\vec{a}.\vec{r} - \vec{a} \tag{3}$$

$$\vec{C} = 2\vec{r} \tag{4}$$

The vector a decreases linearly from 2 to 0 in each iteration, and the vector r is a random vector between 0 and 1 [20].

## 2.4. Bubble-net attacking method

To mathematically model the behavior of bubble-net, two methods are designed as follows:

- Reduce the encircling mechanism: This behavior is achieved by reducing the value in relation 6. It should be noted that the oscillation range $\vec{A}$ is also reduced to a.

- Spiral update position: The spiral equation is between the position of the whale and the position of the prey to mimic the spiral motion of the humpback whale in the form of relations 5 and 6.

$$\vec{X}(t+1) = \overrightarrow{D^{t}} e^{N}.\cos(2\pi l) + \overrightarrow{X^{*}}(t) \tag{5}$$

Where,

$$\vec{X}(t+1) = \begin{cases} \overrightarrow{X^{*}}(t) - \vec{A}.\vec{D} & p < 0.5 \\ \overrightarrow{D^{t}} e^{N}.\cos(2\pi l) + \overrightarrow{X^{*}}(t), & p \geq 0.5 \end{cases} \tag{6}$$

Where *p* is a random number between 0 and 1.

## 2.5. Search for prey

A similar approach based on vector diversity $\vec{A}$ can be used to search for prey. Therefore, this mechanism and $|\vec{A}|<1$, by emphasizing the discovery and allowing the WOA algorithm, leads to a general search. The mathematical model is defined as relations 7 and 8:

$$\vec{D} = \left| \vec{C}.\overrightarrow{X_{rand}} - \vec{X} \right| \tag{7}$$

$$\vec{X}(t+1) = \overrightarrow{X_{rand}}.\vec{A}.\vec{D} \tag{8}$$

Which $\overrightarrow{X_{rand}}$ is a random position vector (a random whale) selected from the current population.

Figure 2 shows the flowchart of the whale algorithm.

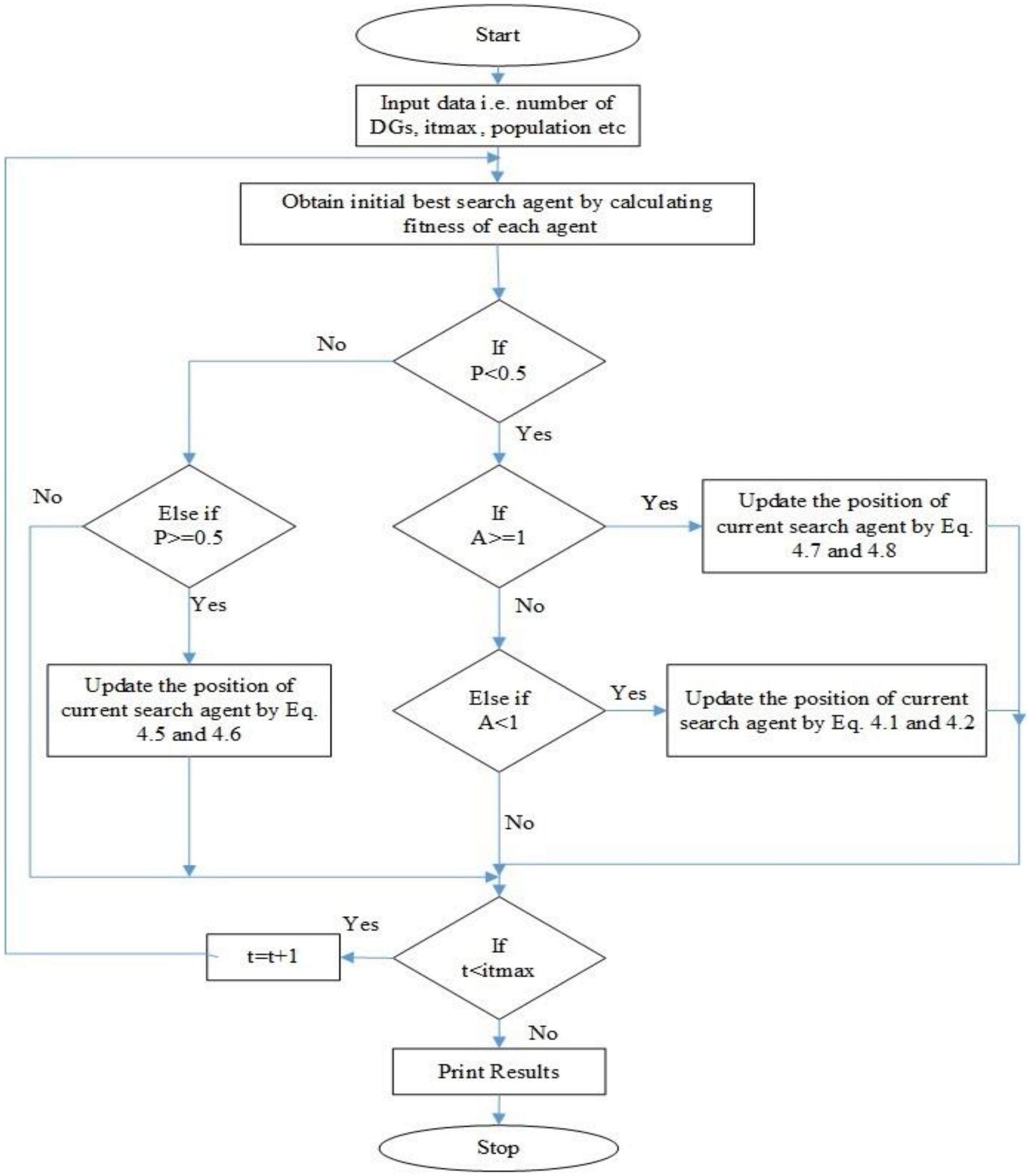


**Fig. 2.** Flowchart of the whale algorithm.

## 2.6. Adaptive neural-fuzzy inference system

This model was developed by Jang in 1993. The appearance of neural-fuzzy models is adaptive to neural network models, i.e. it has a network and layer structure [21]. The ANFIS structure has five layers, which include input, base, intermediate, result, and output nodes and are directly related to each other. Each node has a function with adjustable parameters. The appropriate structure is selected based on the input data, membership degree, input, and output membership rules and functions. In the training stage, by modifying the membership degree parameters based on the acceptable error rate, the input values are closer to the actual values. This model uses neural network learning algorithms and fuzzy logic to design non-linear mapping between input and output space and has good capabilities in training, construction and classification. Also, its learning rule is based on the error propagation algorithm with the view of minimizing the average squares of error between the network output and the actual output [22]. Since this system, uses 0 and 1 degree Sugeno fuzzy model, so the output membership function of the system includes only two constant and linear functions. There is no specific solution to determine the type of input membership function and their degree of membership, and by using trial and error, the best model structure is determined. The ANFIS network operates with a membership function and a low membership rate. Next, using test data sets, network performance is measured relative to data that has not been encountered before. If the test data evaluation criteria are not accepted, the degree of membership of the function is increased and the network training and test steps are repeated. Finally, from the optimal networks related to different membership functions, one network is selected as the top network.

## 2.7. Hybrid model

First, the network data is determined using a matrix in which the sediment data is presented in a curved overflow. Data include training and test data. Using sorted data, ANFIS training begins.

Using the sorted data, ANFIS training begins. The training process allows the system to adjust the parameters defined as the model input or output.

The training process stops when the criteria set for stopping the program are met. After determining the training data, the type of membership functions and fuzzy inference system are optimized by matching the parameters of the membership function. In this study, the whale algorithm is used to determine the parameters related to membership functions in the fuzzy inference system. Next, a vector with $N$ different dimensions is defined as $N$ (number of membership functions). This vector contains the parameters of the membership function, the value of which is optimized using the whale algorithm. The value of the objective function is defined as the function of the mean squares of the error. Also, the search is done to find better responses and to update the best response, and the operations related to the whale algorithm, including jump, intersection and selection, are applied. Next, the value of the objective function is calculated and the stop condition is controlled by considering the convergence and termination of the number of iterations. When the stop conditions are reached, the optimization ends and the optimized values estimate the sediment value using the model test data. Otherwise, the search will continue again to find the best response.

Before continuing the discussion, it is necessary to select the appropriate values for the different parts of the models used, including the initial population, training, and test data, etc. The parameters used in the whale algorithm are presented in Table 3.

**Table 3**
Whale algorithm parameters.

| Parameter | Value |
|---|---|
| Population size | 100 |
| Maximum number of repetitions | 1000 |
| Spiral shape coefficient | 1 |

The numerical values of the parameters presented in table 3 were selected for the whale algorithm, after examining the different values for the parameters and executing the algorithm, the values for these values were selected until the most optimal response was reached.

## 2.8. Problem definition

### 2.8.1. Input structures

In the present study, discharge in t days ($Qr_t$), suspended sediment load in t days ($Sr_t$) were considered as input parameters. Based on the input parameters, three different input combinations were examined to investigate the most effective input parameters (Table 4). It should be noted that all input parameters were used dimensionless.

**Table 4**
Input structures.

| Model | Input parameters |
|---|---|
| $W_1$ | $Qr_t$ |
| $W_2$ | $Qr_{t-1}Qr_t$ |
| $W_3$ | $Qr_{t-1}, Sr_{t-1}Qr_t$ |

### 2.8.2. Performance criteria

The performance of the proposed method was evaluated by two statistics, including the correlation coefficient ($R^2$) and normalized root-mean-square error (NRMSE), as equations 9 and 10:

**- Correlation coefficient**

$$R^2 = \left[ \frac{\sum_{i=1}^{n} \left(Y_i - \overline{Y}\right)(X_i - \overline{X})}{\sum_{i=1}^{n} \sqrt{(Y_i - \overline{Y})^2} \sum_{i=1}^{n} \sqrt{(X_i - \overline{X})^2}} \right]^2 \tag{9}$$

**- Normalized root-mean-square error**

$$NRMSE = \frac{\sqrt{\frac{1}{N} \sum_{i=1}^{N} (X_i - Y_i)^2}}{\overline{X}} \tag{10}$$

In these relations, $X_i$ is the estimated values, $Y_i$ is the observed values, $\overline{X}$ is the mean of X, and $\overline{Y}$ is the mean of Y.

## 3. Results and discussion

In this study, the daily discharge and suspended sediment load of the years 2005-2015 were used as the input of each of the WOA-ANFIS method, and the values of daily suspended load were estimated by these models. At first, all available data were examined with standard normal homogeneity test, which is one of the most commonly used methods for assessing the homogeneity of the data. After introducing the input structures and finding the optimal values of ANFIS parameters and applying them, 80% of the data (172) for training and 20% of the data

(44) were used for model testing. Evaluation criteria for different input structures to estimate the daily suspended load are presented in Table 5.

**Table 5**
Evaluation of input structures.

| Model | Train | | Test | |
|---|---|---|---|---|
| | $R^2$ | NRMSE | $R^2$ | NRMSE |
| $W_1$ | 0.951 | 0.055 | 0.912 | 0.075 |
| $W_2$ | 0.973 | 0.062 | 0.925 | 0.092 |
| $W_3$ | 0.991 | 0.010 | 0.962 | 0.051 |

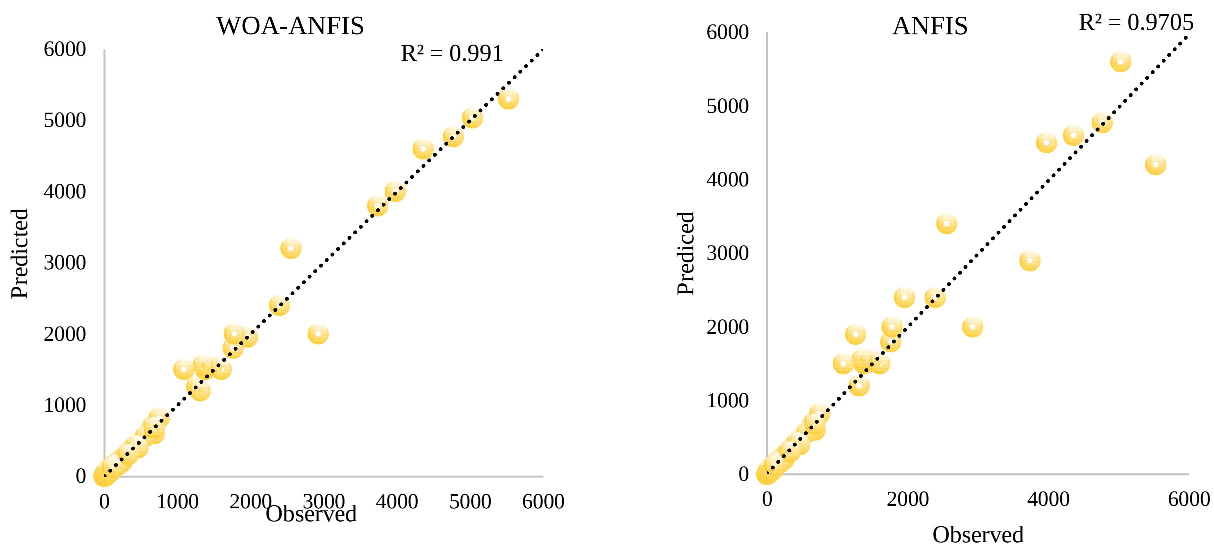


**Fig. 3.** Comparison of observed *SSL* and the predicted *SSL* obtained by WOA-ANFIS and ANFIS on the training stage (Model $W_3$).

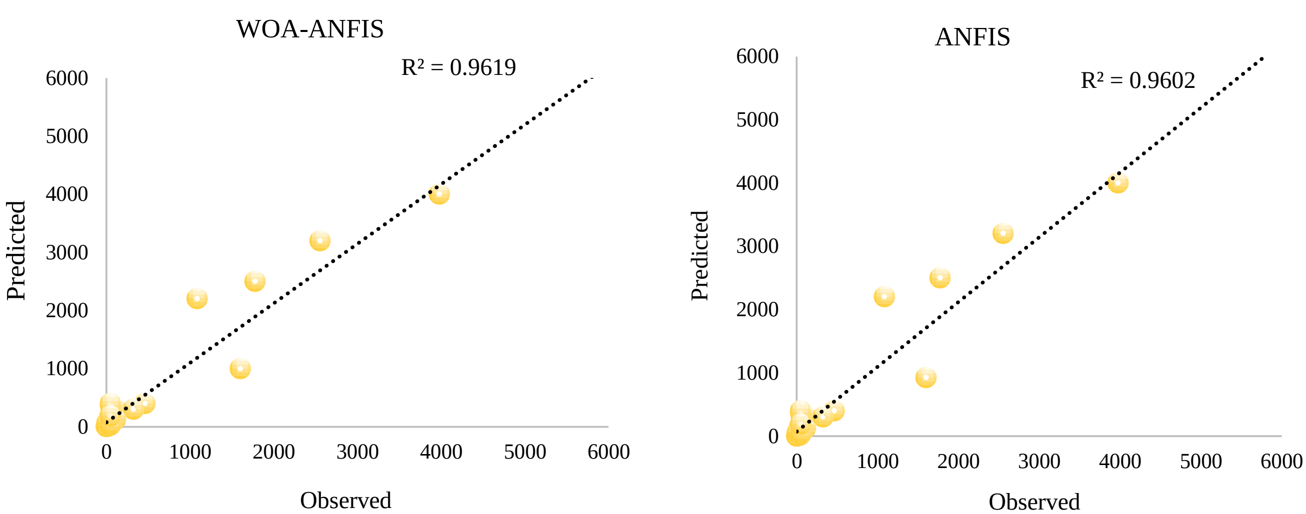


**Fig. 4.** Comparison of observed *SSL* and the predicted *SSL* obtained by WOA-ANFIS and ANFIS on the test stage (Model $W_3$).

According to Figures 3 and 4, it is clear that the *SSL* of the Zarinehrood river using the WOA-ANFIS method is predicted with high accuracy and is in good agreement with observed data. Model $W_3$ also models the *SSL* values with less error according to the input parameters, $Qr_{t-1}$, $Sr_{t-1}$ and $Qr_t$ .

The normalized standard deviation and the number of executable performances in 10 program executions for the WOA algorithm, the maximum *SSL* values and the type and number of membership functions are presented in Table 6.

**Table 6**
Optimal values for 10 times program execution.

| Algorithm | Normalized standard deviation | The number of executable performances | The maximum SSL | Membership functions | |
|---|---|---|---|---|---|
| | | | | Type | Number |
| WOA | 0.0007 | 10 | 98210 | Gaussian | 2 |

As can be seen, the results of the WOA-ANFIS method in estimating the *SSL* of the Zarinehrood river with an $R^2$ of 0.962 are very optimal, which indicates the high efficiency and accuracy of the WOA-ANFIS method.

The maximum estimated sediment and the total volume of the *SSL* are compared by WOA-ANFIS with observed amounts in Table 7.

**Table 7**
Comparison of the maximum estimated sediment with observed amounts.

| Relative error (%) | The results of GWO (ton) | maximum sediment amounts <3000 |
|---|---|---|
| 9.32 | 6380 | 7036 |
| 4.88 | 5220 | 4977 |
| 11.10 | 4560 | 4102 |
| 4.36 | 3640 | 3806 |
| 7.44 | 3470 | 3749 |
| 7.15 | 2950 | 3177 |
| 6.22 | 98210 | 104727 |

Since the estimation of the total volume of *SSL* has a determinant role in water resources management, therefore, the total volume *SSL* is estimated by the WOA-ANFIS method (Table 7). According to the results, it is evident that the estimated sediment value by the WOA-ANFIS method is 98210, which has an error of 6.22% relative to the observed amount, indicating that the maximum estimated sediment amounts and the total volume of *SSL* by the WOA-ANFIS method are consistent with observed amounts.

### 3.1. Comparing the results of this study with previous studies

A comparison of the results of the present study with other studies shows the appropriate accuracy of the proposed hybrid method in estimating the *SLL*. Kisi and Zounemat-Kermani [7], in a similar study, used a new hybrid model based on an evolutionary fuzzy approach (EF) and a genetic algorithm for estimating daily suspended sediment in a river in California, USA. The results of the $R^2$, RMSE, and MAE evaluation criteria for the EF method were 0.91, 4843, and 1604, respectively. Mohammad Rezapour, et al. [23] using the genetic (GA) and particle swarm (PSO) algorithms to optimize the coefficients of the sediment rating curve equation of the Kahak station on the Sistan river and compared the results obtained from these models with the sediment rating curve (SRC). The results showed that in the Kahak station, the GA algorithm with the value of 33484.47 ton/day, the PSO algorithm with the value of 34754.31 ton/day, and the SRC with 35723.90 ton/day, respectively had the RMSE values. Sattari et al. [24] evaluated the performance of the M5 model trees and support vector regression (SVR) in the modeling of *SLL* of Aharchay river. The results of this study showed that the M5 model trees with an $R^2$ of 0.93, and the SVR method with an $R^2$ of 0.89 had a better performance than the conventional sediment rating curve method in estimating the Aharchay river *SLL*. The results of the present study also indicate that the WOA-ANFIS method with $R^2$=0.962 and NRMSE=0.051 has a better performance and can be used as an alternative method in estimating *SSL*.

## 4. Conclusions

The purpose of this study was to use the WOA-ANFIS method in estimating the *SLL* value of the Zarinehrood river in the southeast of Urmia lake, which was based on 10-year data of flow discharge and sediment discharge measured at Sarighamish station on Zarinehrood river. Input structures included discharge and suspended sediment load on the target day. Identifying and selecting the optimal structure for entering data into the WOA-ANFIS method was done using the $R^2$ and NRMSE criteria. 80% of the available data was used to train the model, and the remaining 20% to test the model. The obtained results showed that the WOA-ANFIS method had higher accuracy (with $R^2$=0.962 and NRMSE=0.051 in the test stage) to estimate *SLL*. Therefore, it can be concluded that by choosing the discharge and suspended sediment load on the target day, the best result of the WOA-ANFIS method in the study area can be obtained. In general, it can be concluded that the WOA algorithm has been very efficient in estimating the *SLL*. However, the performance of the WOA-ANFIS hybrid model is not very ideal and for future researches it is better to combine the WOA algorithm with the artificial neural network method and neural-fuzzy models to enhance the completion and accurately estimate the *SLL*.

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## Conflicts of interest

The authors declare no conflict of interest.

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