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Research Article

COMPARATIVE EVALUATION OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS) AND ARTIFICIAL NEURAL NETWORK (ANN) IN SIMULATION OF SUSPENDED SEDIMENT LOAD (CASE STUDY: DALAKI RIVER, CHAM CHIT STATION)

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ABSTRACT
To evaluate mass of sediment carried by rivers, which is important in hydraulic engineering issues, several methods have been presented. Due to the non-linear structure, sediment phenomenon, classic and conventional methods such as rating curve cannot estimate rate of flow of sediments accurately. In this research data for rate of flow of sediment and monthly rate of flow during a statistical period of 21-year was used as an input of model. Through 252 data, which were used in total statistical period, 80% of data for education and 20% for validation selected randomly and Objective Functions of R and RMSE were used for the evaluation of these models. In this research by using Matlab software as well as Artificial Neural Network with sigmund tangent (tansig) function in hidden layer and linear function (Pureline) in output layer and by using information of hydrometer station in Dalaki, Cham Chit, a model has been made for simulation of monthly suspended sediment load and its results compared with Adaptive Neuro Fuzzy Inference System. In all patterns used in monthly scale, performance of Adaptive Neuro Fuzzy Inference System has been better than an artificial neural network.

Keywords: *Neural Network, Suspended Sediment, Adaptive Neuro Fuzzy Inference System, Cham Chit*

INTRODUCTION
Sediment, as a phenomenon, is one of the factors causing quantitative and quantitative crises in surface water, because the mass of sediments affects the mass of input net water to reservoirs, and over time, it reduces the mass of reservoirs and dams (Kia *et al.,* 2012). Investigating river's sediment is a very important task in several cases such as water structures design, flood control, and inundation of rivers (Kia *et al.,* 2012). Considering the importance of sediment and effects of this process on ecology and environment, many researchers have been carried out on this subject worldwide. Specialists of hydraulic science, on the one hand, and experts of hydrology science and watershed, on the other, have studied and examined this process from different aspects and they tried to control sediment and corrosion and decrease adverse effects. Generally speaking, most of these studies have obtained acceptable results. Using artificial intelligence methods including artificial neural network and adaptive neuro-fuzzy inference system, as a powerful instrument, can help determine a type of non-linear relation in complicated processes. Studies which have been done in this regard have estimated the value of suspended sediment in Mississippi, Missouri, Rio Grande Rivers, using artificial neural network modeling (multilayer Perceptron). Following comparison of results with multivariate linear regression model and Arima Model, it was found that neural network model had a higher accuracy than the results of other models (Melsse *et al.,* 2011). In another study, reservoir sedimentation of Duhok Dam was examined using neural network model and conventional models (rating curve). The results showed that neural network model had a better efficiency than conventional methods (Issazadeh *et al.,* 2014). Similarly, for estimation of sediment of Mode River in the United States, artificial neural network and adaptive neuro-fuzzy inference system method were used. Observational data in this research included precipitation data, rate of flow and sediment and neural networks were used such as RBNN and MLP. The results showed that the accuracy of adaptive neuro-fuzzy inference system model was better than common neural networks and conventional method of rating curve (Cobaner *et al.,* 2009). By using daily suspended sediment load and utilizing compound model of adaptive neuro-fuzzy inference system and wavelet, as

well as conventional models (sediment rating curve), daily suspended sediment was calculated at Gagyng station in the United States. In the analysis of Adaptive Neuro-Fuzzy Inference System Model (ANFIS), time series observed of river spill and suspended sediment load were analyzed by wavelet in different scales, and then the total time series affected by spill and suspended sediment load were used as an input in adaptive neuro-fuzzy inference system for forecasting suspended sediment load since the previous day. The results showed that the efficiency of adaptive neuro-fuzzy inference system and wavelet for forecasting was better than that of sediment rating curve (Rajaee *et al.*, 2010). In order to evaluate adaptive neuro-fuzzy inference system in suspended load sediment simulation in Iran, one can point to the comparison of the capabilities of artificial neural network and sediment rating curve in forecasting daily suspended sediment load at Chamanriz station, Kor River. Based on results obtained from artificial neural network, acceptable results were found for suspended load simulation at Chamanriz station, as the comparison of correlation coefficients against existing data of sediment rating curve revealed higher accuracy (Abdi, 2013). In another study, the estimation of rate of flow of suspended sediment at Quran station, Babloord Salon, aided with adaptive neuro-fuzzy inference system was examined. Therefore, one can argue that the accuracy of adaptive neuro-fuzzy inference method is higher than that of the conventional method of rating curve, which is practically used in all corrosion and sediment studies, and this method can be applied to the estimation of river sediment load for water/hydraulic projects (Kia *et al.,* 2012). Moreover, by using adaptive neuro-fuzzy inference system model and sediment rating curve, suspended sediment in Ajichay River was estimated and after comparing results with artificial neural network methods, it was shown that adaptive neuro-fuzzy inference system in comparison to these methods involves a high rate of accuracy (Moaeri *et al.,* 2010).

MATERIALS AND METHODS

The Region under Study

Dalaki River is one of the rivers flowing in Fars and Bushehr Provinces, Iran. The region under study is the drainage basin of Dalaki River in the Basin of Helleh River, with a length of 225 km and 8% average slope (gradient), situated at the 51.46 longitude and at 29.22 latitude. This river, in its general course, which flows south-west, passes through such cities as Kazeroon, Dashtestan, and Bushehr in Fars and Bushehr Provinces, Iran. The area of this basin is 5.190 km^2, and the precipitation rate of the river is measured at Dalaki station. As a result, Dalaki River and its drainage basin are accounted as part of the Persian Gulf Basin and Oman Sea (see Figure 1).

Figure 1: The location of the region under study in Fars and Bushehr provinces

Methodology

In this research, Artificial Neural Network (ANN) and Adaptive Neuro- Fuzzy Inference System (ANFIS) serves as two methods to simulate suspended sediment load, and finally their performances were evaluated and compared, and the optimal method was identified.

Conceptual Foundations and the Artificial Neural Network Theory

Over the past decade, new models called ANN have been introduced to prediction instruments and have yielded acceptable results in various applications. ANN is a simulation of the natural neural system composed of a set of neural units called *neurons* connected to each other through some transmitters called *axons*. The purpose of ANNs is to create a structure similar to the biological structure of the brain and the nervous system, with the same capacities for learning, generalizing, and decision-making. Introducing the history of performance of a mechanical system, such networks seek to store the trained model and system performance and use such information in cases not encountered before.

Another distinctive feature of such models that distinguishes them from other methods and algorithms is their reduced sensitivity to error in inputs. The reason for this is the extended process of distributed information. In this system, complex activities are conducted in an intricately parallel structure, and instead of imposing the entire processing load on only one fast-processing computational unit, several simple computational units jointly undertake the process. This division of tasks brings about another positive consequence: in fact, because a great number of neurons are simultaneously involved in the process, the individual share of each of the neurons would not be a matter of significance. Therefore, occurrence of errors in one of them and their consequences will not perceptibly affect other computational units.

The idea of ANN was introduced in 1940s, when in 1943 McCulloch and Pitts showed that neural networks could compute any arithmetic and logical function. The first scientific application of neural networks was proposed by Rosenblatt in 1958 when multilayer perceptrons networks were introduced. The designed network was capable of distinguishing patterns from each other. Meanwhile, Widrow and Hoff in 1960 proposed Adaptive Linear Neuron or later Adaptive Linear Element (ADALINE), which was structurally similar to the perceptrons networks. Research into such networks continued up to 1986, when Raml *et al.*, (1986) into proposed Back Propagation Algorithm (BPA) theory, constituting a huge development in ANNs and their applications.

To make predictions, back-Propagation Neural Network (BPNN) models involve an input layer, some intermediate layers, and an output layer schematically represented in Figure 2. The number of neurons in each hidden layer is determined through trial and error. To compute their output, neurons pass the inputs through an entrance function. Such functions are divided into some different types including binary, hyperbolic tangent, linear, and Gaussian.

As mentioned earlier, the main elements of a neural network are constituted by artificial neurons. The input model consists of dendritic nodes similar to a biological cell that could be represented as a vector with N items $X= (X_1, X_2, \ldots, X_N)$; the summation of inputs multiplied by their corresponding weights could be represented by scalar quantity S.

Relation (1)

$$s = \sum_{n-1}^{N} W_n X_n = W^T x$$

where $W=(W_1, W_2, \ldots, W_N)$ is the weight vector of associations among neurons. The S quantity is then inserted into a non-linear conversion function *f*, yielding the following output:

Relation (2)

$$\boldsymbol{y} = \boldsymbol{f}(\boldsymbol{s})$$

Non-linear transfer function is usually represented as sigmoid functions and is defined via:

Relation (3)

$$f(s) = (1 + \exp(-s))^{-1}$$

The output of *y* can be the result of the model or that of the next layer (in multilayer networks). In the design of an ANN, certain elements should be taken into account including type of input parameters, number of training data, and structure of the artificial neural network, transfer function, network learning algorithm, and the criteria for selecting the final network.

In this research, the three-layer perceptron network was used which is composed of an input layer, one or several hidden layers of computational modes, and an output layer. In each layer, a number of neurons are considered which are connected to the neurons of neighboring neurons via some associations. In these networks, the effective input of each neuron is the result of the multiplication of the outputs of the previous neuron by the weights of those neurons.

Neurons in the first layer receive the input information and transfer it to hidden neurons through related connections. The input signal in such networks is only expanded in a forward direction. The main advantage of such a network is the simplicity in implementing the model and estimating input/output data. Some of the major shortcomings of this model are the low training rate and the need for a huge bank of data. In Figure 2, a sample of a three-layer ANN is illustrated.

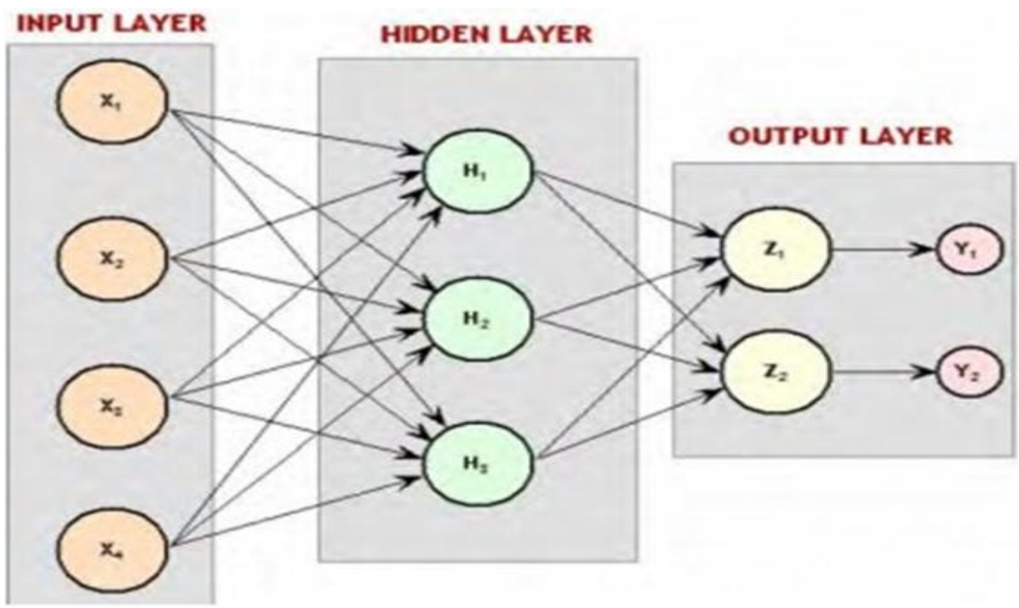

Figure 2: A schematic representation of a three-layer ANN

Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS models were first developed by Jang (1993) and incorporate fuzzy logic with ANN to facilitate the learning process and enhancing adaptation.

As such, ANFIS relies on the fuzzy If-Then rule statements, as the main problem in formulating fuzzy systems, to develop an effective tool, which uses ANN learning ability for automatically creating such fuzzy statements and optimizing the parameters.

In fact, the ANFIS model is a neuro-fuzzy approach.

For the sake of simplification, one can assume that the inferential system has two inputs, X and Y, and an output Z. For a first-order Takagi-Sugeno fuzzy model, a set of basic rules can be founded upon two rules, if the fuzzy system shows the following:

$$z_1 = p_1x + q_1y + r_1$$
$$z_1 = p_2x + q_2y + r_2$$

- Rule 1: if X is equal to A_1 and Y is equal to B_1, then….
- Rule 2: if X is equal to A_2 and Y is equal to B_2, then….

if p_i, q_i, and r_i (i=1,2) are the linear parameters in the consequent section of the first-order Takagi-Sugeno fuzzy model. The ANFIS structure is composed of 5 layers (see Figure 3).

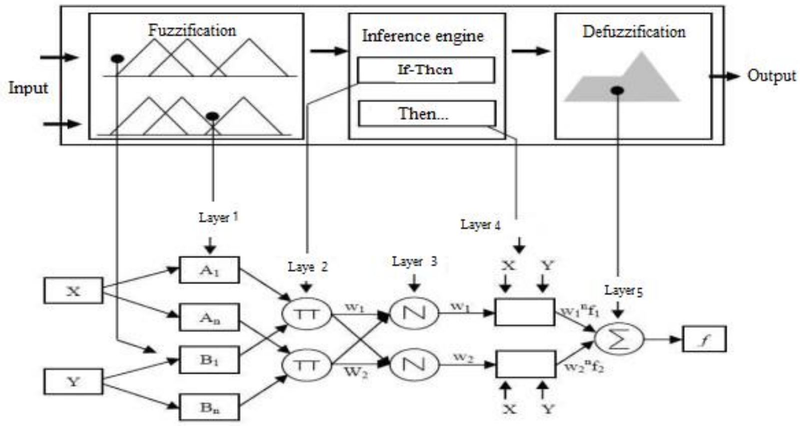

Figure 3: ANFIS model structure

- Input nodes (first layer): each layer of this node produces membership values belonging to each of the soundly fuzzy sets via membership function:
Relation 4

$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$

Where *x* and *y* are non-fuzzy inputs related to i, A_i, and B_i (small, larger, etc.) as linguistic labels which are respectively identified through μ_{A_i} and μ_{B_i} appropriate membership functions. At this stage, Gaussian fuzzification and bell-shaped functions are usually used. The parameters of these membership functions, which are recognized as primary parameters, should be first identified.
- Rule nodes (second layer): in the second layer, the operator "AND" is used to find the output (firing strength) which represents the antecedent of the rule. Firing strength is used to describe the degree to which the antecedent satisfies a fuzzy rule, shaping the output function of the same rule. As a result, $O_{2,k}$ outputs of this layers, are the results of the multiplication of the degrees related to the first layer.
Relation (5)

Average nodes (third layer): the main purpose in the third layer is to determine the ratio of *i*-th rule firing strength to the total firing strength. Therefore, $\overline{W}_i$ the normalized firing strength would be as follows:
Relation (6)

$O_{3,i} = \overline{W}_i = \frac{w_i}{\sum_{k=1}^{4} w_k} \qquad i = 1, \dots, 4$

- Consequent nodes (fourth layer): the node function of the fourth layer calculated the distribution of *i*-th rule in the final output, defining it as the following relation:
Relation (7)
$O_{4,i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) i = 1, \dots, 4$
where $\overline{w}_i$ is the output of *i*-th node from the previous layer. $\{p_i, q_i, r_i\}$ are coefficients of this linear combination as well as the set of parameters of the consequent part of the Takagi-Sugeno fuzzy model.
- Output nodes (fifth layer): this single node computes the total output by summating all of the input signals. As a result, in the layer of the defuzzification process, the fuzzy results are converted into non-fuzzy formats.
Relation (8)

$$O_{5,i} = \overline{W}_i f_i = \frac{\sum_{i=1}^{4} w_i f_i}{\sum_{i=1}^{4} w_i}$$

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This network is trained based on learning under supervision. Thus, the focus of this study is on training adaptive networks capable of estimating unknown functions resulted from training information and finding accurate values for the above parameters.

Statistical Assessment of the Research Results

In this study, to assess the results of the two models, correlation coefficient (R) and root-mean-square error (RMSE) were used as criteria.

Relation (9)

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

Relation (10)

$$R = 1 - \frac{\sum_{i=1}^{N}(o_i - t_i)^2}{\sum_{i=1}^{N}(o_i - \bar{o}_i)^2}$$

RESULTS AND DISCUSSION

Methods and Results

Considering research purposes, data related to sediment discharge and flow discharge were sorted per month (March 1989 - February 2009) and were separately inserted to the ANN (80% for training the network and 20% for testing the network). Then, the results obtained from the neural network were compared against existing real results based the evaluation criteria (R and RMSE), and ANFIS was used to create different models for simulating suspended sediment.

Clearly, MATLAB provides various membership functions for the ANFIS system including Gaussian, triangle, and so on, out of which *gaussmf* was selected based on a trial and error method. Values of R and RMSE for simulation of suspended sediment load for ANN and ANFIS systems are illustrated in Tables 1 and 2. Furthermore, from among different models of the ANFIS system, for Model 5 RMSE was found 0.107 and R was 87.34, as the best model. Similarly, from among the ANN models, for Model 2 RMSE was 0.184 and R was 48.27, as the weakest model.

ANFIS

Modeling sediment discharge through different models

Model 1: Q
Model 2: Q, Q_{-1}
Model 3: Q, Q_{-1}, Q_{-2}
Model 4: Q, Q_{-1}, Q_{-2}, Q_{s-1}
Model 5: Q, Q_{-1}, Q_{s-1}, Q_{s-2}
Model 6: Q, Q_{-2}, Q_{s-2}
Model 7: Q, Q_{-1}, Q_{-2}, Q_{s-1}, Q_{s-2}

Table 1: Different models of discharge and sediment discharge

Discharge/ sediment discharge	**Membership Function**	**Epochs**	**Error**	**R**	**RMSE**
Model 1	gaussmf	30	0.1486	73.605	0.148
Model 2	gaussmf	30	0.1449	75.451	0.144
Model 3	gaussmf	30	0.1354	78.522	1.136
Model 4	gaussmf	30	0.1036	85.299	0.115
Model 5	gaussmf	30	0.0959	87.349	0.107
Model 6	gaussmf	30	0.1401	77.102	0.14
Model 7	gaussmf	30	0.0588	84.12	0.127

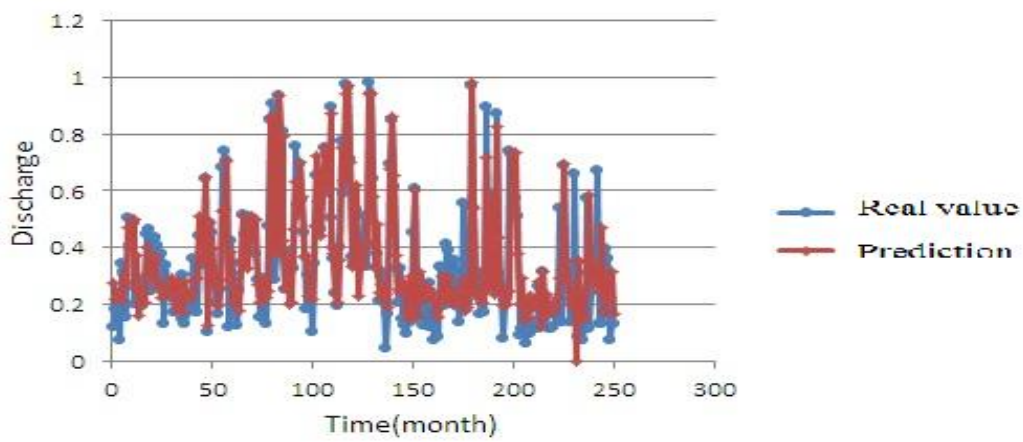

Figure 4: Model 5 of discharge and sediment discharge

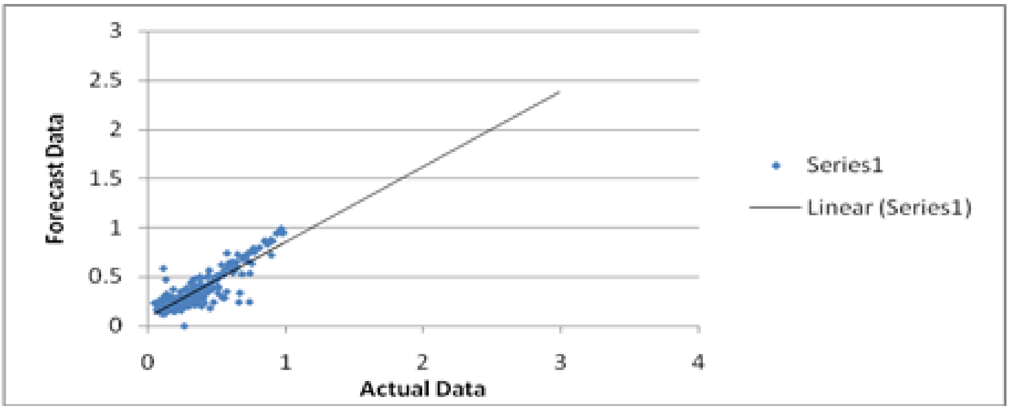

Figure 5: The diagram of frequency for Model 5

ANN

Modeling sediment discharge through different models

In this method, the same 7 models in the ANFIS were used. In this method, the sigmoid tangent function "*tansig*" was used in the hidden layer and the linear function "*purelin*" was used for the output layer, for the second and third structures of the layer. As mentioned above, for Model 2 RMSE was found 0.184 and R was 48.27 and it was found to be the weakest model along with structure 1.4.8 (see Table 2).

Table 2: Different models of discharge and sediment discharge

Discharge/ sediment discharge	**Structure**	**Transfer Function**	**Epochs**	**Goals**	**R**	**RMSE**
Model 1	10-5-1	TANSIG	10000	0.001	50.66	0.166
Model 2	8-4-1	TANSIG	10000	0.001	48.27	0.188
Model 3	10-1	TANSIG	10000	0.001	65.44	0.14
Model 4	7-4-1	TANSIG	10000	0.001	61.21	0.131
Model 5	4-1	TANSIG	10000	0.001	62.44	0.132
Model 6	4-2-1	TANSIG	10000	0.001	74.58	0.121
Model 7	6-2-1	TANSIG	10000	0.001	65.38	0.128

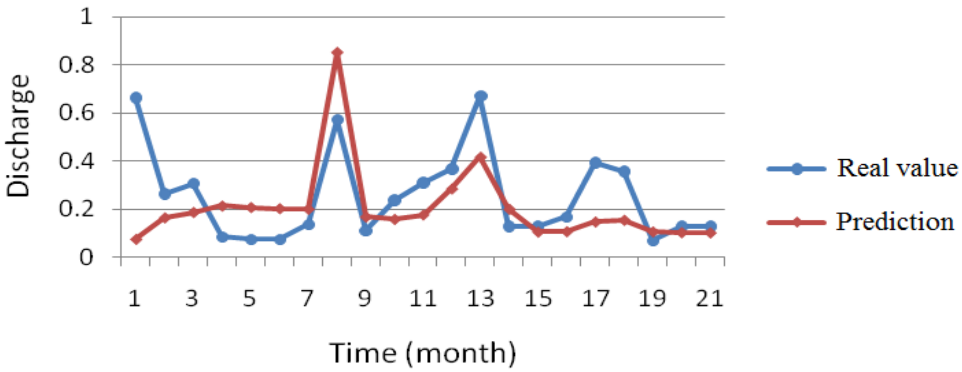

Figure 6: Model 2 of discharge and sediment discharge

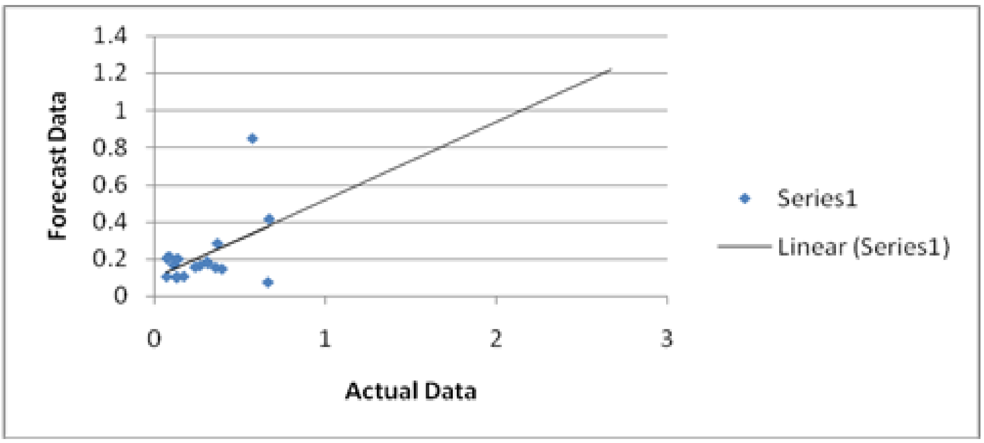

Figure 7: The diagram of frequency for Model 2

Conclusion

Considering the significance of simulating suspended sediment load in rivers, from different perspectives, finding an appropriate method for this purpose can be a considerable contribution. Modeling and simulating through artificial intelligence, if its complexities are overcome, can provide a especial application. In this research, a comparative assessment of ANFIS and ANN systems was made to evaluate their performance in simulating suspended sediment. In doing so, monthly sorted data related to sediment discharge and flow discharge was extracted from the Chamchit Station situated in Dalaki River. The general comparison of the findings revealed that the accuracy of the ANFIS model in estimating suspended sediment load was more acceptable than that of ANN.

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