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Suspended Sediment Concentration Estimation using Artificial Neural Networks and Fuzzy Rule Base Model Case Study: Jagin Dam

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ABSTRACT

Simulation and sediment assessment of the river are of the significant and practical issues in water resource management. To estimate the suspended sediment concentration of Karaj dam in this study, simultaneous water discharge data, base, water temperature and sediment density of Siraa Station located at Karaj dock entry have been used. fuzzy rule base, Artificial Neural Network (ANN) and Sediment Rating Curve (SRC) modeling was used. Correlation coefficient (R^2) and Root Mean Square Error (RMSE) are considered the model's assessment criteria. The results show a higher accuracy of fuzzy model assessments in comparison with neural networks and sediment rating curve assessments.

Key words: Sediment, fuzzy rule base, artificial neural network, Jagin Dam.

INTRODUCTION

The prediction of sediment load and its variability in rivers is an essential component in water resources m models have been developed to simulate this process anagement. The sediment transport in basins and rivers is a complex hydrological process and many [12]. Each model has its own advantages and limitations, but due to the large number of parameters involved, the theoretical governing equations may not be of much use for gaining knowledge of the overall process.

Recent literature reviews reveal that computational intelligence approaches have been successfully used for modelling and prediction of water resources variables. The ANN-based modelling approach for hydraulic and hydrological phenomena is discussed in detail by the ASCE Task Committee.

Fuzzy logic is another area of computational intelligence that has been applied successfully in different water resources and environmental fields which include: rainfall–runoff modelling [8] and reservoir operations [13].

In recent years, fuzzy rule base have found a broad range of engineering applications that require analysis of uncertain and imprecise information. ANN and fuzzy rule base are complementary approaches in the design of adaptive intelligent systems. NF models have been applied to a number of water resources problems, including evaporation simulation [15] and river flow modelling [3].

Cigizoglu [5] made a comparison between ANNs and SRC for suspended sediment estimation and found that the estimations obtained by ANN's were significantly superior to the corresponding classical sediment rating curve ones.

Agarwalet *et al* [2] simulated the runoff and sediment yield using artificial neural network as daily, weekly, ten-daily, and monthly monsoon runoff and sediment yield from an Indian catchment using back propagation artificial neural network (BPANN) technique, and compared the results with observed values obtained from using single- and multi-input linear transfer function models. They showed that the ANN model gives pretty reliable results.

Kisi [9] investigated the abilities of neuro-fuzzy (NF) and neural network(NN) approaches to model the stream flow– suspended sediment relationship for two stations—Quebrada Blanca station and Rio Valenciano station—operated by the US Geological Survey. He found that the NF model gives better estimates than the other technique.

Ebrahimi M [6] compared in an article the efficiency of artificial neural network models,

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multivariate regression and sediment rating in assessing the daily suspended loading of Koreh Sang Station located at Haraz River based on daily precipitation and discharge as well as taking into consideration the RMSE and R criteria which indicate a better performance of artificial neural network models. Nourani *et al* [14] introduced a model based on fuzzy logic structure to estimate sediment suspended load of Khaivchay River located at Ardebil province which had a better results in comparison with classical methods and also artificial neural networks.

In this study, a new approach based on an adaptive artificial neural network**s** and fuzzy rule base approach is presented for prediction of suspended sediment concentration in the Penhan gauging station .Tow modele ANN and Fuzzy rule base are trained using measured water and sediment discharge data of Penhan gauging station which is located at the entrance of Jagin dam in Iran.

Materials And Methods

2.1. Geographical Position of the Study Area:

The study area of this research is Jagin dock. Jagin dock is located at the permanent Jagin River which is considered the part of Jagin catchment. Considering geographical position, this basin is located between260 59' 40" to 260 4 '5" latitudes and 570 42' 40" to 570 57'.19" in the East of Hormozgan. Also, the space of this area has been calculated with Arc GIS 10.3 software which the extent of basin is hereby 3899 square kmeters .

2.2. Data collection:

The measured data of Penhan station between 1985 and 2012 is used to train developed ANN, FLR and fuzzy rule base models. Of course, the relation of sediment and water discharge differs in Penhan and the gauging station used naturally one of the problems faced with studying this kind.

2.3.Models Employed:

In this study three intelligent models FRBM, FLR and ANN were used to estimate the Suspended sediment

2.4 Assessment Indicators:

To assess the performance of constructed prediction models in this study, three statistical indicatorshave been used:

2.4.1 Correlation coefficient according to relation (2).

$$CORR = \frac{\sum_{i=1}^{n}(x_i^o - \overline{x}^o)(x_i^p - \overline{x}^p)}{\sqrt{\sum_{i=1}^{n}(x_i^o - \overline{x}^o)^2 \sum_{i=1}^{n}(x_i^p - \overline{x}^p)^2}}$$

2.4.2 Error square mean root according to relation (3).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(x_i^o - x_i^p)}{n}}$$

2.5artificial neural network model:

An ANN consists of a number of data processing elements called neurons or nodes that are grouped in layers. The input layer neurons receive input data or information and transmit the values to the next layer of processing elements via connections.

This process is continued until the output layer is reached. This type of network in which data flows in one direction (forward) is known as a feedforward network. The application of ANN models has been the topic of a large number of recent literatures, such as the book by Lingireddy and Brion [10].

A model of a neuron has three basic parts: input weights, a summer, and an output function:

The input weights scale values used as inputs to the neuron, the summer adds all the scaled values together, and the output function produces the final output of the neuron. Often, one additional input, known as the bias is added to the system. If a bias is used, it can be represented by a weight with a constant input of one. Figure 1 shows a simple ANN with three inputs and one output

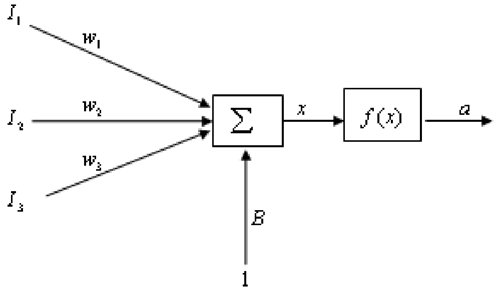

Fig. 1: A schematic neuron model.

I , 2 I and 3 I are the inputs, 1 w , 2 w and 3 w are the weights, B is the bias, x is an intermediate output, and a is the final output. The equation for a is given by

$$a = f(w_1 I_1 + w_2 I_2 + w_3 I_3 + B)$$

where f is a transfer function. Detailed information can be found in related literature such as Lingireddy and Brion [10].

2.6 Fuzzy Rule Base MODEL:

Fuzzy rule-based models developed by Lotfizadeh [11] for handling imprecise information, has found important application in various fields including water based systems in the last five decades. Introduction of Linguistic Terms (LT) by Grima [7] and application of complex mathematical models by Broomhead *et al* [4] have established this methodology as a reliable tool for predicting water resource parameters. A FRBM contains membership functions of fuzzy sets constructed on the range of all the inputs to the model. The model matches the input and output, which also contains membership functions, with fuzzy rules .In this study, as suggested by Broomhead *et al* [4].

Results and discussion

For calculating Suspended sediment in fuzzy rule base, Artificial Neural Network (ANN), Excel and MATLAB softwares are used respectively. RMSE and R2 were used for validation and approval of the results.

3.1 FRBM design:

In the design of the FRBM, five inputs containing Same-day discharge(Q), Days prior to discharge(Q-1), Two days prior to discharge(Q-2), Scale water of the Day(H) , Scale water days ago(H-1) were considered and Suspended sediment was the model output. In order to establish the rule-bases, 80 lines of the data containing inputs and outputs were selected randomly. following a local search on the four available membership functions of triangular, bell-shaped, dome-shaped and inverted cycloid, the triangular input membership function was selected based on the lowest root square mean error (RSME) of 1.065 and highest R2 of 0.9132 as shown in Table 1.

Table 1: Comparison of membership functions type used in FRBM.

Number	Membership Function Type	RMSE	R2
1	TRI-MF	1.065	0.9132
2	TRAP-MF	1.21	0.821
3	GBELL-MF	1.43	0.886
4	GAUSS1-MF	2.01	0.856
5	GAUSS2-MF	1.74	0.794

Membership Function Type: TRI: triangular, TRAP: Trapezoid, GBELL: generalized bell, GAUSS, GAUSS2-MF: Gaussian

Five FRBM models (FRBM-1 to FRBM-5) were defined based on the quantity of linguistic terms and also, the type and number of input parameters mentioned above (see Table 2). Using 5 similar input parameters, FRBM-1, FRBM-2 and FRBM-3 have been defined with 2, 3 and 5 LT respectively, and as suggested by Figures 1 to 6, FRBM-1 with 2 LT showed the least RMSE of 1.021. FRBM-4 and FRBM-5 were hence defined using 2 LT but different types and number of input parameters. Based on the results demonstrated in Table 2, FRBM-1 with lowest RMSE, with input triangular membership function and 2 LT was selected as the best FRBM for this study.

Table 2: Characteristics of various FRBM's defined for this study.

parameters	FRBM-1	FRBM-2	FRBM-3	FRBM-4	FRBM-5
Same-day discharge	*	*	*	*	*
Days prior to discharge	*	*	*		*
Two days prior to discharge	*	*	*	*	*
Scale of the Day	*	*	*	*	
Scale days ago	*	*	*	*	*
RMSE mm/day	1.021	1.33	1.51	1.82	1.75

3.2 Artificial neural network design:

The proper structure used for modeling the issue of sediment density is the networks with progressive orders that multi-layered Perspstron (MLP) network has been used in this study. The general configuration of this network is five entries of Same-day discharge(Q), Days prior to discharge(Q-1), Two days prior to discharge(Q-2), Scale water of the Day(H) , Scale water days ago(H-1) and a sediment discharge output. The input layer includes five neurons that receive Same-day discharge(Q), Days prior to discharge(Q-1), Two days prior to discharge(Q-2), Scale water of the Day(H) , Scale water days ago(H-1) and is resulted into output layer of sediment discharge. There are also various neurons in the hidden layer. The function of these units' activities in this layer is hyperbolic tangent function. The output of this layer is limited to 1 and -1. Linear activation function has been used in the output layer for increasing the network speed. Not only dose using the linear function increase learning speed several times, but it can provides the output values without making any change in the network. Learning methods of MLP network is based on the post-observance error algorithm. There are three learning methods for this regard which Markowart-Lonburgh method is the fastest of them and the present network has been trained by this algorithm. Various neurons have been used in the hidden layer and the number of their optimums for minimizing the error should be determined by trial and error. The network is first trained by little neurons in the hidden layer and the number of neurons gradually increasesand the network will be re-trained. Because the initial selection of weight and threshold is randomly in each training stage and this issue causes the network is located at different initial conditions, so each structure has been tested by different initial structure in order to ensure not to falling into local minimums and gaining universal minimum [1]. The comparison of results of ANN models with measured data are denoted in figures7.

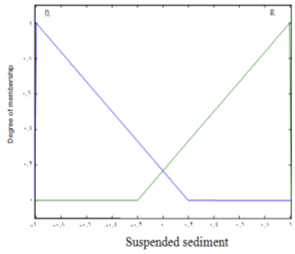

Figure۱: Membership function, model FRBM-۱, with ۲ linguistic terms

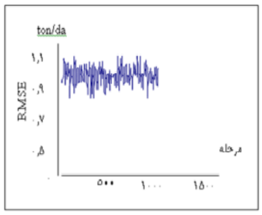

Figure ۲: RMSE for model FRBM-۱, with ۲ linguistic terms

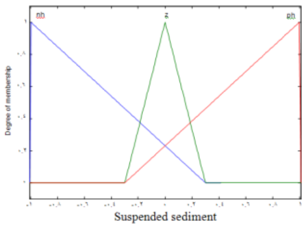

Figure ۳: Membership function, model FRBM-۱, with ۳ linguistic terms

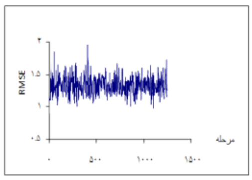

Figure ۴: RMSE for model FRBM-۱, with ۳ linguistic terms

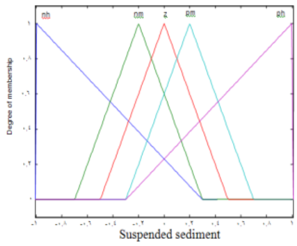

Figure۵: Membership function, model FRBM-۱, with ۵ linguistic terms

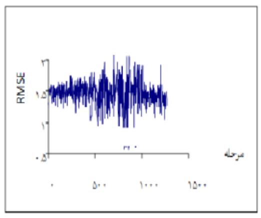

Figure ۶: RMSE for model FRBM-۱, with ۵ linguistic terms

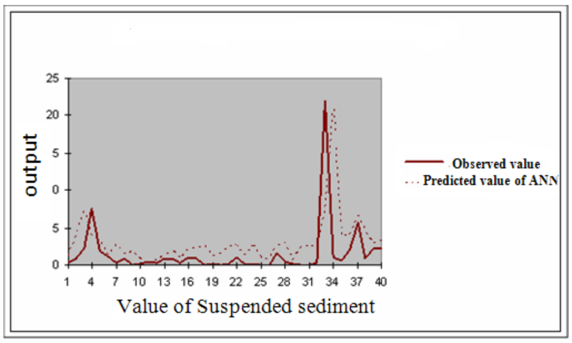

Fig. 7: Comparison of ANN result with measured data.

Table 4: Comparison of RMSE and R2 for ANN and FRBM.

parameter	FRBM-1	FRBM-2	FRBM-3	ANN
RMSE(mm/day)	1.021	1.33	1.51	1.065
R2	0.934	0.846	0.832	0.913

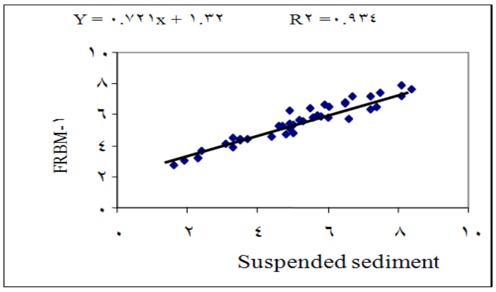

Fig. 7: Comparing observational and estimated Suspended sediment using FRBM–1 model.

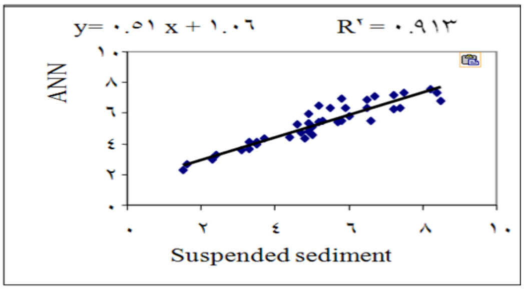

Fig. 8: Comparing observational and estimated Suspended sediment using ANN model.

Conclusion:

RMSE and R2 were used to select the best method to determine Suspended sediment amongst FRBM and ANN. As can be seen from Table 4, the results indicate that R2 good (0.832 to 0.934), while RMSE alters more so that the least RMSE relates to FRBM model with two linguistic terms (FRBM-1), followed by ANN, FRBM-2, FRBM-3, which showed higher RMSE (RMSE altered in the range of 1.02 to 1.51).

Considering Figures 7 and 8 in which the observed and estimated Suspended sediment are demonstrated using the two models FRBM and ANN proved to be the best method. fuzzy rule-based model is proposed to be used for Suspended sediment estimation of the region.

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