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Full Length Article

Using Intelligence Models to Estimate Suspended sediment system case study: Jagin Dam

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ABSTRACT
Sediments are transferred by the rivers due to passing from sedimentary basins and cause erosion of the sides and bottom and also sedimentation throughout its course. 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 Jagin dam in this study, simultaneous water discharge data(Q), Scale water (H) and sediment density(Qs) of Penhan Station located at Jask dock entry have been used. fuzzy rule base, Artificial Neural Network (ANN) and FLR Sediment Rating Curve (SRC) modeling was used. Correlation coefficient (R) and Root Mean Square Error (RMSE) are considered the model's assessment criteria The results show a higher accuracy of fuzzy rule base model assessments in comparison with neural networks and FLR sediment rating curve assessments.
Keywords: Sediment, fuzzy, artificial neural network, Sediment rating curve

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INTRODUCTION
Although suspended sediment load can be predicted using numerous developed equations their results often differ from each other and from measured data due to complexity of sediment transport nature. In recent years, simulation models for prediction of suspended sediment load of rivers have been popular among researchers because of Progress of computer models[2]. Artificial Neural Networks (ANN) and Artificial Neuro-Fuzzy Inference Systems (ANFIS) are two well-known models for prediction of hydraulic and hydrology events. Many researchers have studied the application of Artificial Neural Networks in vital topics of hydrology and hydraulics such as prediction of sediment load, rainfall-runoff modeling, flow prediction etc [7].

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 [1] 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 [11] 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, 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 [15] 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.
The scope of this study is the suspended sediment estimation of Jagin dam using an intelligent method to get more accurate results compared to the rating curve. Three ANN , FLR 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

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 between 260 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 [12].

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.

MODELS EMPLOYED

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

Fuzzy Rule Base

Fuzzy rule-based models developed by Lotfizadeh [20] 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 [8] 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], 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.

Tabl e 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

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.
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.

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

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

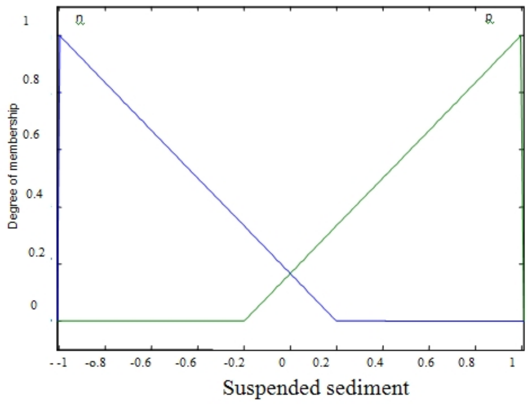

Figure 1: Membership function, model FRBM-1, with 2 linguistic terms

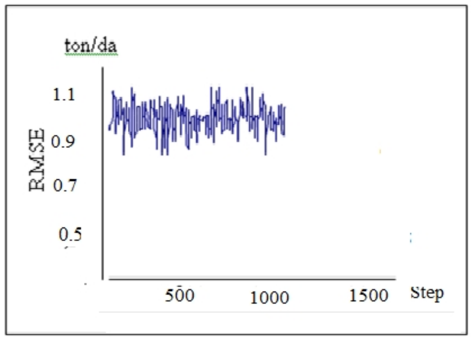

Figure 2 : RMSE for model FRBM- 1, with 2 linguistic terms

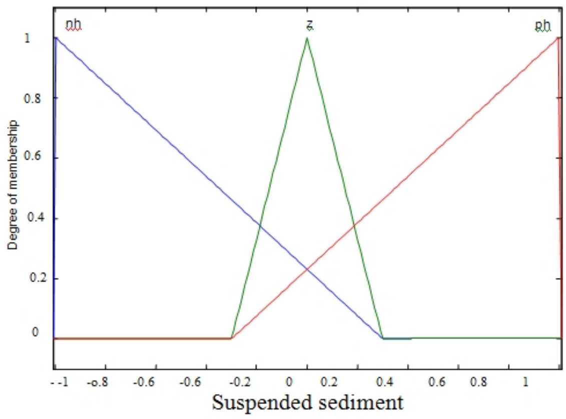

Figure 3 : Membership function, model FRBM- 1, with 3 linguistic terms

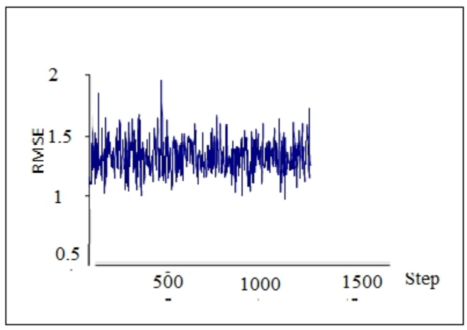

Figure 4 : RMSE for model FRBM- 1, with 3 linguistic terms

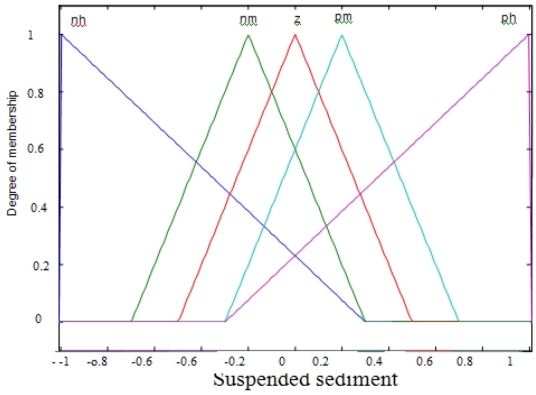

Figure5: Membership function, model FRBM- 1, with 5 linguistic terms

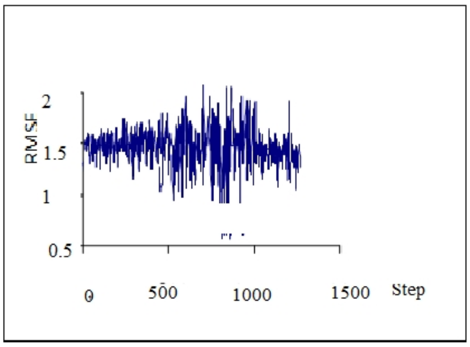

Figure 6: RMSE for model FRBM-1, with 5 linguistic terms

Artificial Neural Network method

The modern view of ANNs began in the 1940s with the work of McCulloch and Pitts. ANNs are mathematical models consisting of highly interconnected processing nodes or elements (artificial neurons) under a pre-specified topology (sequence of layers or slabs with full or random connections between the layers). In 1950s Rosenblatt built many variations of a specific type of early neural computational models called perceptron network and developed associated learning rules which led to introduction of first practical application of ANN. They have been used extensively since 1980's in a variety of diverse real world applications **[11].** In this work, the multi-layer perceptron network has one input layer (with three processing elements), one hidden layer (with two processing elements) and one output layer (with one processing element).

Fuzzy Linear Regression

In regression analysis, the best mathematical expression describing the functional relationship between one response and one or more independent variables are obtained. Following the introduction of the fuzzy theory, by Lotfizadeh, fuzzy regression model (FLR) was developed by Tanaka et al [18] in which fuzzy uncertainties of dependent variables with the fuzziness of response functions were explained. Based on the conditions of variables, there are 3 categories of FLR: a) input and output data are both non-fuzzy numbers, b) input data is non-fuzzy number but output data is fuzzy number, and c) input and output are both non-fuzzy number . Estimation of FLR. though being the subject of continuous research, is often carried out by two techniques, e.g.: fuzziness minimization by numerical method using linear programming and deviation minimization between the estimated and observed outputs, sometimes referred to as fuzzy least square method.

FLR has been used where response variable is in intervals. By taking mean or mode, interval value can be changed to crisp values but at a cost of losing useful information about the spread. Hence, no proper interpretation of the fuzzy regression interval can be made . Tanaka's approach, referred to as possibilitic regression has also been criticized for both not being based on sound statistical principles [20], as well as creating computational difficulties when large number of data points is encountered. Yager [19] reported that fuzzy linear regression (FLR) may tend to become multicollinear as more independent variables are collected. The draw back, on the other hand, with the fuzzy least square method is the spread of estimated response increases as the magnitude of explanatory response increases, even though the spread of observed responses are roughly constant or decreasing. To overcome this, Setnes [17] proposed a "two-stage" approach for fitting fuzzy linear regression (FLR) through fuzzy least square approach and showed superiority over Diamond's procedure. This approach is discussed by [20], and relevant nonlinear computer programs such as LINGO, have been developed to solve such cases. As far as fuzzy nonlinear regression is concerned, Sanchez [16] proposed "evolutionary algorithm solutions" in which for a given fuzzy data, algorithm searches from a library of fuzzy functions (including linear, polynomial, exponential and logarithmic) one which would fit the data. In this study, using HYDROGENERATOR and LINGO softwares, a fuzzy possibilistic model was employed in which coefficients are fuzzy, while inputs and outputs are non-fuzzy observational. The model used may be represented by the following equation:

$$\tilde{y} = \tilde{A}_0 + \tilde{A}_1 x_1 + \tilde{A}_2 x_2 + \tilde{A}_3 x_3 + \dots\dots\dots + \tilde{A}_n x_n$$

where, $\tilde{A}_0, \tilde{A}_1, \dots, \tilde{A}_n$ are fuzzy coefficients and $x_1, x_2, x_3, \dots, x_n$ are observational input variables which are normal numbers and $\tilde{y}$ is the fuzzy output for each variable n. Table 3 shows the object function and the restrictions used for the FLR in this work.

Table 3: Linear programming model for solving linear regression with non-fuzzy observations.

Fuzzy a linear regression:	$\tilde{y} = \tilde{A}_0 + \tilde{A}_1 x_1 + \tilde{A}_2 x_2 + \dots + \tilde{A}_n x_n$
function:	$\text{Minimize } : \text{mc}_0 + \sum_{j=1}^{m}\sum_{i=1}^{n} c_i \lvert x_{ij} \rvert$
Limits:	$p_0 + \sum p_i x_{ij} - (1-h)\left[c_0 + \sum c_i x_{ij}\right] \le y_j$ $p_0 + \sum p_i x_i + (1-h)\left[c_0 + \sum c_i x_{ij}\right] \ge y_j$

RESULTS AND DISCUSSION

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

Sensitivity Analysis

A sensitivity analysis was required to indicate which one of the input parameters has more important role on defining the Suspended sediment in the models. This is carried out in two following methods: addition of input parameters and removal of input parameters. Accordingly, whichever parameter whose addition or removal would causes the most reduction in RMSE would be identified as the most sensitive parameter. In this work, using the latter approach, one of the five input parameters was removed at a time and the corresponding RMSE was calculated as shown in Table 4. Same-day discharge(Q) was therefore found to be the most sensitive parameter in all methods used while, the Scale of the Day(H) showed the least sensitivity in FRBM, and Days prior to discharge(Q-1)was the least sensitive for ANN and FLR.

Table4: Sensitivity Analysis

Input Parameters	FRBM RMSE(mm/day)	ANN RMSE(mm/day)	FLR RMSE(mm/day)
(Q), (Q-1), (Q-2), (H), (H-1)	0.73	0.86	0.79
(Q), (Q-1), (Q-2), (H)	0.93	0.77	0.95
(Q), (Q-1), (Q-2), (H-1)	0.90	0.99	0.96
(Q), (Q-1), (H), (H-1)	0.96	0.75	0.87
(Q), (Q-2), (H), (H-1)	0.88	0.93	0.90
(Q-1), (Q-2), (H), (H-1)	1.17	1.47	1.26

CONCLUSION

RMSE and R2 were used to select the best method to determine Suspended sediment amongst FRBM, ANN and FLR. As can be seen from Table 4, the results indicate that R2 good (0.824 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, FLR, FRBM-2, FRBM-3, which showed higher RMSE (RMSE altered in the range of 1.02 to 1.51).

Table 4: Comparison of RMSE and R2 for ANN, FRM and FRBM

parameter	FRBM-1	FRBM-2	FRBM-3	ANN	FLR
RMSE(mm/day)	1.021	1.33	1.51	1.065	1.16
R2	0.934	0.846	0.832	0.913	0.824

Considering Figures 7, 8 and 9 in which the observed and estimated Suspended sediment are demonstrated using the three models FLR, FRBM and ANN, fuzzy rule-based model. proved to be the best method. fuzzy rule-based model is proposed to be used for Suspended sediment estimation of the region.

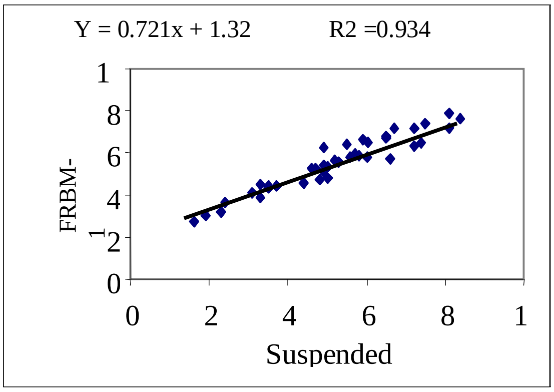

Figure 7: Comparing observational and estimated Suspended sediment using FRBM–1 model

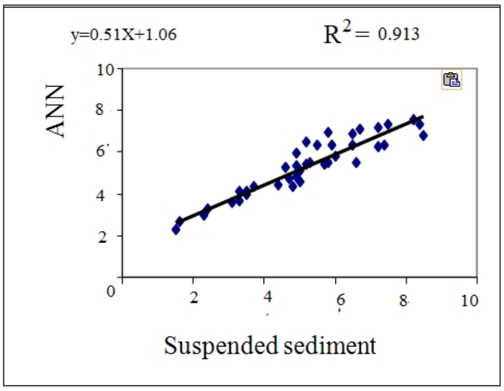

Figure 8: Comparing observational and estimated Suspended sediment using ANN model

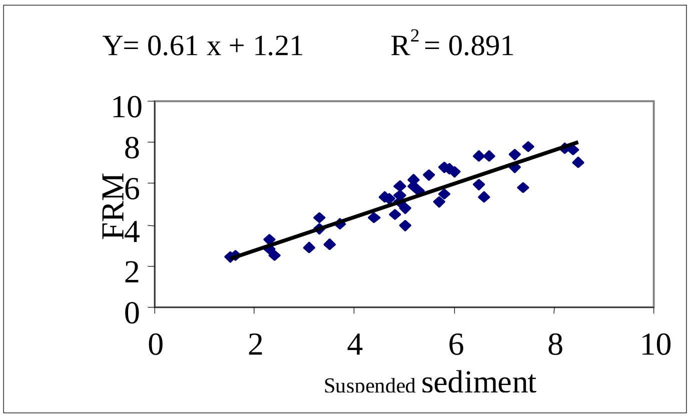

Figure 9: Comparing observational and estimated Suspended sediment using FRM model

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