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Suspended load routing using artificial neural network and 1D fully coupled model (Case study: Ahwaz Station, Karoon, Iran)

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ABSTRACT

Sediment load estimation is one of the challenges of river engineering. More researches have been conducted to develop a perfect model to sediment transport simulation. Analytical and data-driven models are two main groups of models. In this paper, one dimensional fully coupled model and artificial neural network models performance is compared in sediment rating curve simulation in Ahwaz station, Karoonriver, Iran. 1D fully coupled model has calibrated and validated using Nash-Sutcliffe coefficient. The magnitude of 0.15 and 0.19 of NS coefficient for calibration and validation periods of coupled model represent good agreement of the model with average condition of river. According to calculation, derived sediment rating curve using ANN with FFBP algorithm, has good agreement with measured rating curve. In high flows, both two models have difference with measured data. In general ANN model has more accuracy than coupled model.

Key words: *Suspended load, Fully coupled model, Artificial neural network, Sediment rating curve, Karoon river,*

Introduction

Surface erosion and sediment transport have been research issues for more decades due to their economic and cultural developing importance. Erosion and sedimentation are two phenomena which occur in river such as flow condition variation leads to change in their effective parameters and vice versa. On the other words, stream flow and sediment transport are simultaneous phenomena. Theoretical analysis of sediment transport is conducted in simple condition due to its highly complex nature (Wu, 2007).

Performance and reliability of models for sediment transport estimation are depending to modality of simulation. Sediment transport models are categorized in two groups: (1) models based on dynamic and fluid mechanics rules, (2) data-driven models. Time and dimension are two important criteria for the first group classification. For more engineering applications, cross sectional properties of sediment and flow is important. 1D model requires the least amount of field data and numerical schemes used for solving the water and sediment governing equations are more stable and offer order of magnitude gains in computational time over 2D and 3D models. 1D models simulate the flow and sediment transport in the stream wise direction of a channel without solving the details over the cross section (see for example Kassem and Chaudhry, 1998; Cao *et al.*, 2002). A model was developed by Wu *et al.* (2006) for unsteady flow condition in canal network. They showed that the model can predict flow and sediment characteristics accurately. Zhi *et*

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al. (2006) developed fully coupled model for sediment transport based on mixing length theory. There was good agreement between laboratory and field data. Conroy *et al.*, (2006) used 1D model for sediment transport rate in forest catchment. Huybrechte (2008) developed a 1D fully coupled model to study sediment rate in Yellow River. The model has acceptable results with measured data. Because of unknown effective factors in sediment transport simulation, the application of the second group of models has been developed. The simplest example of a data-driven model is provided by a linear regression where a single input variable (e.g. wave height) is used to provide an estimate of the predicted variable (e.g. sediment transport rate). Many different (and more complicated) data-driven algorithms have been developed and Artificial Neural Networks (ANNs) are an excellent example of such algorithms (Maanen *et al.*, 2010). ANNs algorithm was applied for the first time by French (1992) for water resource issues (French *et al.*, 2003). Basics and principles of ANNs wasdescribed in hydrology and hydrogeology studies through a paper by ASCE. In recent years, the successfully application of ANNs in sediment transport simulation has been reported through various researches: Nagy *et al.*, 2002; Merritt *et al.*, 2003;Cigizoglu, 2004, Kisi, 2004; Agarwal *et al.*, 2005; Rai and Mathur, 2008; Wang and Traore, 2009; Rajaee, 2011;Wang *et al.*, 2012; Adid and Jahanbakhahan, 2013; Fuladipanah and Sangi, 2013).

As it shown, in recent years 1D model have wide application in sediment transport simulation. The most 1D models have been derived based on Navier-Stocks equation which has complex numerical solution. It is worthwhile to develop a model using control volume concept which will have the least complexity. Fuladipanah *et al.* (2010) developed 1D fully coupled one. Their model has the following four main factors. First, many scientific problems can't be solved by neglecting flow dynamic, i.e. assuming the balance existence between exerted forces to flow, which are leaded to the normal flow). But their model is a fully dynamics one. Second, flow and sediment transport are time dependent processes. Empirical relationship often do not satisfy this dependence. Hence, calculation of flow and sediment properties at arbitrary time, is the model's grant. Third, as mentioned foreside, the complexity of interaction between flow and sediment transport make it difficult to describe this coupled phenomena. In this model based on conservation rules, this phenomenon has been modeled explicitly. Forth, in many early models, it is assumed that the actual sediment transport rate is equal to the capacity of flow sediment at equilibrium condition at each cross section. However, alluvial river systems always change in time and space due to many reasons; therefore, absolute equilibrium state rarely exists in natural condition. The local equilibrium assumption is not realistic, particularly in case of strong erosion and deposition. According to successful application of ANNs in sediment transport prediction, a comparison between 1D fully coupled and ANN capability has been done in this paper. For actual comparison, simulated rating curve from these two models was compared with measured one in Karoon River, Ahwaz station, Iran (Fig. 1).

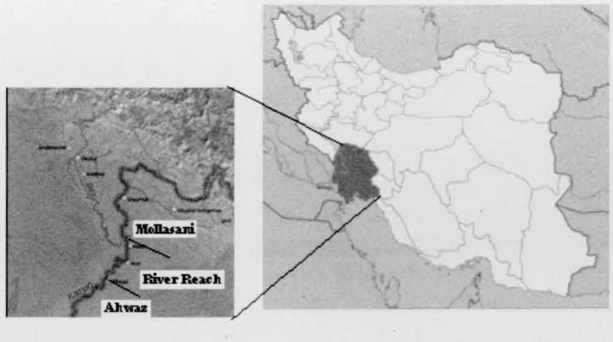

Fig. 1. Karoon River, Ahwaz and Mollasani Stations

Materials and Method

1D Fully Coupled Model

Model equations are derived based on following assumptions: (1) the main part of sediment load is suspended; (2) there is no abrupt contraction or expansion in undertaken reach; (3) pressure has hydrostatics distribution; (4) suspended load routing can be simulated using diffusion model. Based on these assumptions, continuity and momentum conservation lows were derived using control volume concept and Reynolds transport theorem as following, respectively:

$$\frac{\partial A}{\partial t}+(S-1)\frac{\partial (CA)}{\partial t}+\frac{\partial (AU)}{\partial x}+(S-1)\frac{\partial (ACU)}{\partial x}=0 \quad ..(1)$$

$$\frac{\partial (UA)}{\partial t}+(S-1)\frac{\partial (UCA)}{\partial t}+\frac{\partial (AU^2)}{\partial x}+(S-1)\frac{\partial (ACU^2)}{\partial x}+gA\frac{\partial y}{\partial x}+g(S-1)CA\frac{\partial y}{\partial x}=gA(S_f-S_o)(1+(S-1)C) \quad (2)$$

Where x and t are space and time variables, respectively, A is cross section area, S is specific gravity of sediment particle, U is mean velocity, C is sediment concentration by weight, g is gravity acceleration, y is flow depth, S_f is energy line slope, S_o is bed slope. According to the fourth assumption, diffusion equation was used to sediment concentration routing:

$$\frac{\partial C}{\partial t}+U\frac{\partial C}{\partial x}=D_x\frac{\partial^2 C}{\partial x^2} \quad ..\ (3)$$

Where D_x is diffusion coefficient. Flow depth, y, flow velocity, U, and sediment concentration, C, are three variables which should be determined in each time step. Manning roughness coefficient, n, and diffusion coefficient, D_x, are two constants, which should be determined during calibration period.

Equations (1) to (3) are partial differential equations with non-analytical solution. Implicit finite difference scheme was used to discretize numerical solution.

ANNs Model

The concept of using Artificial neural network is not new, but its application began from about 1946 by a person named Hu, who used it to predict the weather. ANN is one of the artificial intelligence varieties which act generally as man brain. The system is composed of a large number of processing elements called neurons. ANN provides a random mapping in between an input and an output vector by mimicking the biological cognition process of our brain. Each typical ANN contains three layers of neuron including: input layer, hidden layer, and output layer(referring to Fig. 2).

These neurons are interconnected, but independent computational unit which works as the following equation:

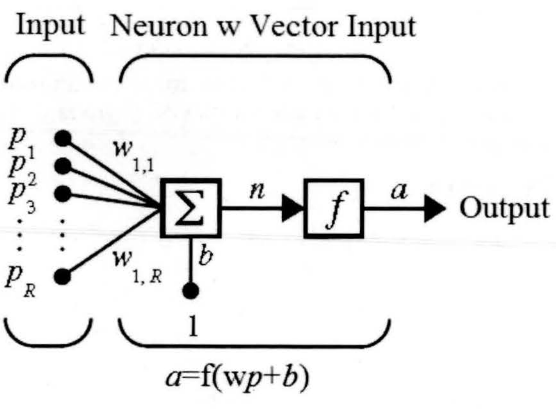

Fig. 2. Working of a neuron

$$a=\sum_{i=1}^{R} w_{1,i}p_i+b\sim f(Wp+b) \quad ..\ (4)$$

Which p_i is input values, $w_{1,i}$ is connection weights that determines the strength of connection, b is bias value which increases the net input to the activation function and therefore accelerate the error convergence, f is threshold function. The threshold functions usually have a sigmoid shape (Rezaeianzadeh *et al.* (2010), Jalalkamali and Jalalkamali (2011), chang and Liao (2012), Dorofki *et al.* (2012), Moharampour *et al.* (2012)) with the following definition:

$$f=\frac{1}{1+\exp(-z)} \quad ..\ (5)$$

$$z=\frac{x-x_{min}}{x-x_{max}} \quad ..\ (6)$$

where z is normalized input data. In ANN the models are mostly prepared in two stages: training and validating. Usually 70 to 80 percent of measured data are used in training stage. Therefore, 20 to 30 percent of data will be applied in validating stage. Network training using available data is the first step to provide ANN. Training comprises presentation of input and output pairs to the network and fixing the values of connection weights, bias or centers. The training may require many epochs (presentation of complete data sets once to the network). Generally, the network is presented with the input and output pairs until the training sum-square error reach the error goal in order to give the desired network performance. Error back propagation is one type of training which has more application in engineering problems. This network is trained for feed forward back propagation (FFBP) Figure 3 shows the architecture of network.

After each training process, predicted values have been compared with real or observed ones. Statistical indicators such as, correlation coefficient (R), root mean square error (RMSE), mean absolute error (MAE),average absolute relative error (AARE). These four statistical indicators are used to evaluate effectiveness of the proposed method considering following measured data using following equations:

$$R=\frac{\sum_{i=1}^{n}(x_{obs}-\bar{x}_{obs})(x_{est}-\bar{x}_{est})}{\sqrt{\sum_{i=1}^{n}(x_{obs}-\bar{x}_{obs})^2(x_{est}-\bar{x}_{est})^2}} \quad ..\ (4)$$

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_{obs}-x_{est})^2} \quad ..\ (5)$$

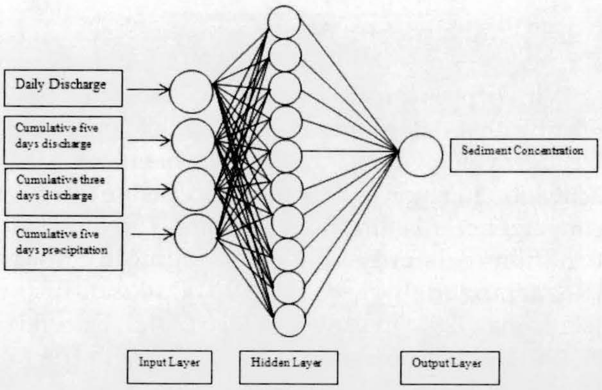

Fig. 3. Architecture of ANN

$$MAE=\frac{1}{n}\sum_{i=1}^{n}\left|x_{obs}-x_{est}\right| \quad .. (6)$$

$$AARE=\frac{1}{n}\left[\sum_{i=1}^{n} 1-\frac{x_{est}}{x_{obs}}\right] \quad .. (7)$$

In the above equations, x_{obs} is the observed parameter, x_{est} used for predicted parameter and n is the numberof available data.

Results and Discussion

1D Fully Coupled Model Performance

As mentioned, Ahwaz station in Karoonriver has been selected for the case study. For model running, Mollasani station was selected as upstream boundary condition. Flow and sediment transport rate was simulated for 365 days from 22 September 2003 to 21 September 2004. This time has complete data recording. Doing calibration period for the first 120 days, Manining roughness coefficient was determined 0.028 (Fig. 4).

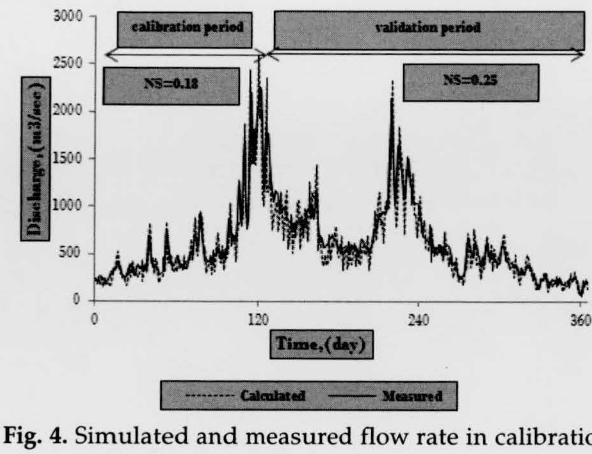

Fig. 4. Simulated and measured flow rate in calibration and validation periods

The Nash-Sutcliffe coefficient (NS) of model efficiency was used as a statistical criterion for evaluating hydrodynamic goodness of fit between measured and calculated values for each variable, which is recommended by American Society of Civil Engineers Watershed Management Committee for evaluating the performance of models that simulatecontinues hydrograph. It defines as following:

$$NS=1-\frac{\sum_{i=1}^{n}(Q_{obs_i}-Q_{est_i})^2}{\sum_{i=1}^{n}(Q_{o_i}-\bar{Q}_o)^2} \quad .. (8)$$

Where Q_o is measured discharge value, Q_{est} is simulated values of flow discharge and n is the number of data pairs. The perfect fit between measured and simulated values would plot as 1:1. A value of zero suggests that the fit is as good as average value of all the measured data for each event, indicating a poor model fit. Negative NS values (having no lower limit), generally considered meaningless, indicate poor predictive value of model, with negative values indicating a poorer model fit. Table 1 shows some statistical properties of sediment load during calibration and validation periods. Measured versus simulated values of sediment concentration is plotted in Fig. 5.

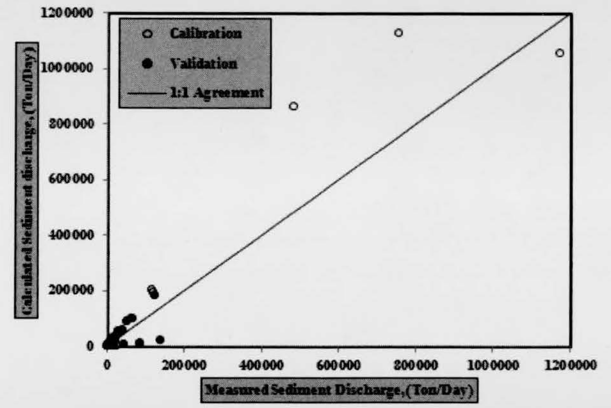

Fig. 5. Measured vs. simulated sediment concentration during calibration and validation periods

ANN performance

Out of the 365 data, 80% selected for training process, and the rest were applied for model validation.Normalized data were used for ANN model in the range (0,1). Logsigmoid and Tansigmoid activation function were selected for hidden and output layer of FFBP model, respectively. Tansigmoid and Purline activation function were selected for hidden and output layer of CFBP model. Logsigmoid, Tansigmoid, and Purline activation functions have the following expression:

$$a=\frac{1}{1+e^{-n}} \quad .. (10)$$

$$a=\frac{e^{n}+e^{-n}}{e^{n}-e^{-n}} \quad .. (11)$$

Table 2 shows the model architecture selection criteria. Results of ANN performance are presented in Table 3.

Simulation of sediment rating curve

As mentioned, the result of coupled model and ANN model has been compared in simulated sediment rating curve. Figure 6 shows measured sediment rating curve in Ahwaz station. In this figure, three trend-line of power type have been drawn. The coefficients of power type trend-line are presented in Table 4.

As it clear, 1D fully coupled model has good agreement in low flow, but there is more difference in high flow. In high flow, the amounts of bed resistance and dispersion coefficient are different from normal flow condition. Also, the prismatic assumption of channel section (no abrupt contraction and expansion) may insert errors in numerical output of model. The difference between ANN output and measured data is very low, although in high flows this is significance. According to Fig. 6, fitness in average condition is reasonable for two models.

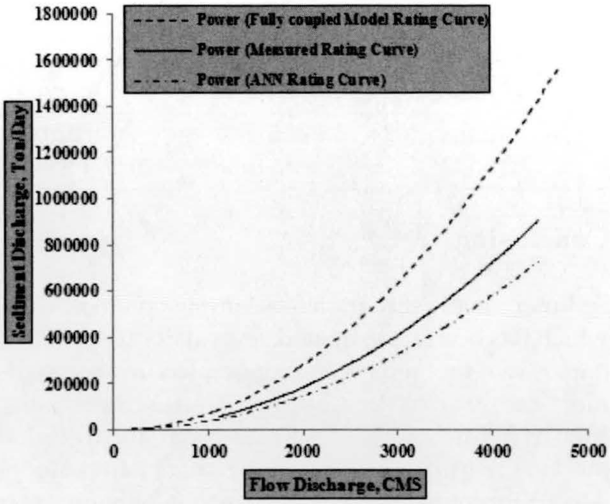

Fig. 6. Simulated VS. Measured sediment rating curve in Ahwaz station

Table 1. Measured and calculated values of suspended load concentration on Ahwaz station

	Calibration Run		Validation Run	
	Measured	Calculated	Measured	Calculated
Number of values	93		20	
Average(ton/day)	35486	45583	34083	35752
Maximum	1170556	1127771	140588	126529
Minimum	1260	204	1054	1581
Sum	3300187	4239198	681656	715041
Standard deviation	150676.7	181781.4	40966.5	42245.85
NS coefficient	0.15	0.19		

Table 2. Statistical criteria to select acceptable architecture

Number of hidden layers	Number of nodes	R	RMSE	MAE	AARE
1	3	0.3875	125.3	89.6	0.72
1	5	0.5548	98.4	63.1	0.57
1	7	0.7369	25.1	11.4	0.29
1	10	0.9233	4.6	2.1	0.1

Table 3. Network configuration

Algorithm	Network configuration			Epochs
	Input nodes	Hidden nodes	Output nodes	
FFBP	4	10	1	89

Table 4. The coefficients of trend-line equation ($Q_s=aQ^b$)

	1D Fully coupled model rating curve	Measured rating curve	ANN rating curve
a	0.106	0.0537	0.0407
b	2.123	1.9788	1.986

Conclusion

Sediment load estimation is a complex phenomenon which has been investigated several decades. In this paper, two methods were applied to simulate sediment rating curve in Ahwaz station, KaroonRiver, Iran; as following: (1) one dimensional fully coupled model, (2) artificial neural network. The first model was calibrated and validated during 23 September 2003 to 22 September 2004. The NS coefficient was used to determine the best performance of the model. According to Table 2, the amount of NS coefficient was calculated for calibration and validation period 0.15 and 0.19, respectively. On the other words, this model simulates the average condition of river. In high flows, the accuracy of model decreases (Fig. 6). The ANN model was applied in two algorithms: FFBP and CFBP. With trial and error process, 10 nodes were selected for hidden layer. The correlation of coefficient between measured and calculated data is 0.9233. According to Fig. 6, the ANN has very good agreement with measured data. Although in high flows its accuracy decreases. In general it can be said that 1D fully coupled model and ANN model can simulate average condition of sediment load estimation. But, in high flows, the ANN model has high accuracy.

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