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Comparison of Sediment Prediction Based on Neural Network and Bagnold formula

(A case study; Bazoft River)

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Abstract

Predictions of suspended sediment load for Bazoft River in Iran using selected empirical equation and Neural Network were made based on 171 sets of data. This river is one of the rivers which is categorized under small rivers with width to depth ratio smaller than 5. Data covers flow discharges from 5.11 m^3/s to 49.55 m^3/s, flow velocities from 0.27 m/s to 1.53 m/s, flow depths from 0.39 to 0.71 m. The paper examines whether a neural network (MLP) can predict the suspended sediment discharge in the river better than the formula. The results of the formula evaluation showed thatBagnold cannot estimate the suspended sediment discharge exactly.The results of neural network method showed that MLP hasgood performance in suspended sediment estimation in comparison with Bagnold formula. What can be said is that MLPusing water discharge as an individual input parameter and also considering1 input layer, 3 hidden layers and1 output layerhad the best performance among all of the models of neural network. Evaluation showed RMSE= 0.0315 and R^2= 0.966 which is recorded the highest determination coefficient.

Keyword: Suspended sediment, Neural Network, Bagnold formula, Bazoft River

1. Introduction

Improving knowledge on suspended sediment yields, dynamicsand water quality is one of today's major environmental challengesaddressed to scientists and hydropower managers (Owens et al.,2005). Indeed, estimates of suspended sediment load are essential for the river transportation investigation. According to Altunkaynak (2009), estimation of sediment load is required in practical studies for the planning, design, operation and maintenance of water resources structures. The sediments transportation monitoring requires a good sample technique which is very lengthy and costly (Pavanelli and Palgliarani, 2002). The emergence of ANN technology has given many promising results in the field of hydrology and water resources and also sediment hydraulic for solving the nonlinear system complexity problem (Sudheer*et al.,* 2003; Adeloye and Munari, 2006). The hydrological characteristics of the river such as the temporally and spatially changing of sediment concentrations, and the difficulties for their estimation encouraged the employment of the ANN models. In the river sediment loads modeling study during storm events of short duration, Rai and Mathur (2008) found the neural network as a suitable estimation tool in two catchments areas of United

States of America. These advances will continue in the future as the acquisitionof reliable and long-term suspended sediment concentration (SCC)time series are generalized to many hydrometric stations. In mountainouscatchments, major fractions of the annual suspended sedimentyields (SSY) are transported over a very short time periodgenerally corresponding to several floods (e.g. Meybeck et al., 2003; Mano et al., 2009). Therefore high-frequency SSC monitoringis required for reliable SSC and SSY estimates. Nevertheless, a reliableand easy method to obtain a direct, continuous SSC measurementis not currently available. Although great progress isexpected with, for instance, the backscatter acoustic method(Wren et al., 2000; Gray and Gartner, 2009), their application is stilllimited to large rivers and canals.Work on quantification of fine-grained sediment movement based on the time-dependent, advection-dispersion equation was presented by Scarlatos and Li (1992). Erosion and sediment transportation determination are the important matters in watershed management. Management of watershed can be easier if the amounts of sediment discharges in rivers are measured very accurately (Olive and ET al, 1992). On the other hand suspended sediment estimation is the most important problem, because there are so many groups that need this kind of data (Hicks and ET al, 2000).The development of hydraulic sediment occurs in response to needs of the active programs of waterresources projects. Most of the information concerning the feedback effect of sediment transport on flow characteristics relates to the case of suspended sediment (Omid ET al, 2010). A number of sediment transport models and formulae can be found in the literature that is used to study sediment transport in alluvial channels. Most of the transport models are based on simplified assumptions that are valid in ideal laboratory conditions only and may not be true for much complicated natural river systems. Models based on more sophisticated theoretical solutions require a large number of parameters that are impossible or difficult to collect for a natural river system (Choudhury and SundarSil , 2010). Xia et al. (2010) compared four different methods of determining bank full discharge in the lower Yellow River and found that a method using a stage–discharge relation from one-dimensional hydrodynamic - model is of higher prediction accuracy than the other three methods. Eder and et al(2010), compared five different methods and also integrated models of calculating SSC in a classic non-linear optimization setting, which allows gauging their relative merits and showed that for the calculation of the total of suspended sediment, application of a single event rating approach was already sufficient to obtain reliable event loads with respect to the observed benchmark turbidity data. Tena et al (2011) found that calculations of sediment load are based on continuous discharge and turbidity records, the latest calibrated with direct suspended sediment sampling that covered the whole range of observed hydraulic conditions. Gao, (2011) found that in practice, theempirical equation can be used to estimate the maximum possible bed-load transport rates during highflow events, which is useful for various sediment-related river managements.Kisi (2010) compared three methods of neural network with each other, a comparison of results indicated that the NDE models give better estimates for suspended sediment in river than NF, NN and RC techniques. In this paper, predictions of suspended sediment for BazoftRiver were made and analyzed using the selected equation and Neural Network.

2. Methodology

2.3 ARTIFICIAL NEURAL NETWORKS AND MODELS EVALUATION

The artificial neural network (ANN) is a massively parallel-distributed information processingsystem that has certain performance characteristics resembling to the biological arrangementof neurons in human brain (Kumar *et al.*, 2008**)**. An ANN establishes a data-driven nonlinearrelationship between inputs and outputs of a system. Thus, neural networks

(NN) have been successfully applied in a number of diverse fields including waterresources. In the hydrological forecasting context, artificial neural networks (ANNs) may offer a promisingalternative for rainfall–runoff modeling Shamseldin (1997),Tokar and Johnson (1999), Wilby*et al*. (2003),Solomatine and Dulal (2003)), streamflow prediction Clair and Ehrman (1998); Shivakumar*et al*. (2002),Cigizoglu (2003) ;Chibanga*et al*., 2003; Kisi, 2004a;Kerem Cigizoglu and Kisi (2006) andreservoir inflow forecasting . There are few published works in the field of suspended sediment data predictionusing artificial intelligence methods such as neural networks and fuzzy logic approach Alp and Tayfur (2002), reviewed the ANN-based modeling in hydrology over the last years, andreported that about 90% of the experiments extensively make use of the multi-layer feed-forward neuralnetworks (FNN) trained by the standard back propagation (BP) algorithm. Maier & Dandy (2000) reviewed 43papers dealing with the use of the ANN model for the prediction and forecasting of water resources variables. The neural network typicallyconsists of an input layer, an output layer and a layer of nonlinear processing elements,known as the hidden layer. The ANN has several algorithms used in forecasting and modeling processes. In this study, the feed forward back propagation (BP) algorithm was selected for modeling the suspended sediment concentration.The most commonly used artificial neural network in hydrological predictions is the BPalgorithm (Kerh and Ting, 2005). BP is a supervised learning technique used for training theneural networks. Basically, it is a gradient descent technique to minimize some error criteria.BP has been widely used in approximating a complicated nonlinear function. The BP networkstructure in this study possessed a three-layer learning network consisting of an input layer, ahidden layer and an output layer.

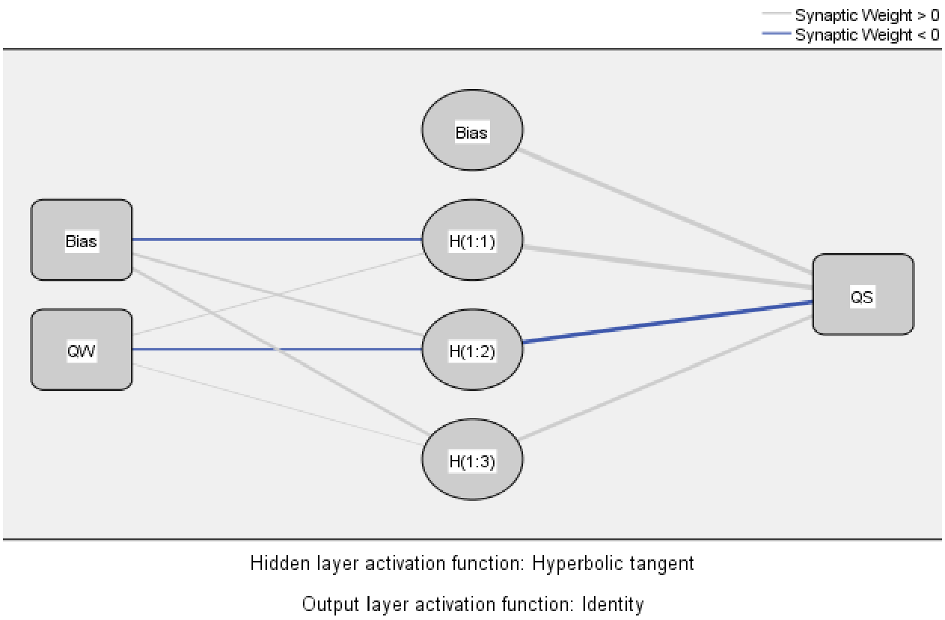


Figure 1: Schematic diagram of BParchitecture

Improving the Generalization level in Model

One of the most important and effective problems that occur during neural network training is over fitting. The error on the training set is driven to a very small value, but when new data is presented to the network the error is large. The network has memorized the training examples, but it has not learned to generalize to new situations (Haghizadeh et al, 2010).The feed forward back propagation (BP) algorithm is a widely applied three layers network type consisting of an input layer, a hidden layer and an output layer. The determination of the number of nodes in a hidden layer providing the best training results was the initial process of the training procedure. The suspended sediment concentration estimation was carried out with the BP by considering the width and depth and also the area of the river, water discharge and velocity as associate inputs of the network. Various hidden nodes numbers were tried for the BP algorithm.

Model Evaluation:

The performances evaluation criteria were the root mean square errors (RMSE) and the coefficient of determination (R^2) expressed between estimated and observed suspended sediment concentration as:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} d_i^2}{N}} \tag{1}$$

Where di is the difference between *i*th estimated and *i*th observed values of suspended sediment concentration and *N* is the number of observations. The coefficient of determination used to evaluate the performance of the models is defined as follows:

$$r^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - y_i')^2}{\sum_{i=1}^{N} (y_i -)^2} \tag{2}$$

Where $y_i$and y_i' are the *i*th observed (actual) and estimated values of y, and y is the meanof the observed values of y; and N is the number of observations.

2.1 Study area

Application of the suspended sediment estimation formula and Neural Network are tested in Bazoft River in Iran.Sediment dischargeand sediment concentration and also water discharges series for the stations are used to developand verify models performances. The drainage area of this river is about 2355 km^2 and the station that these data are used from, is located in 913 meters higher than see level.

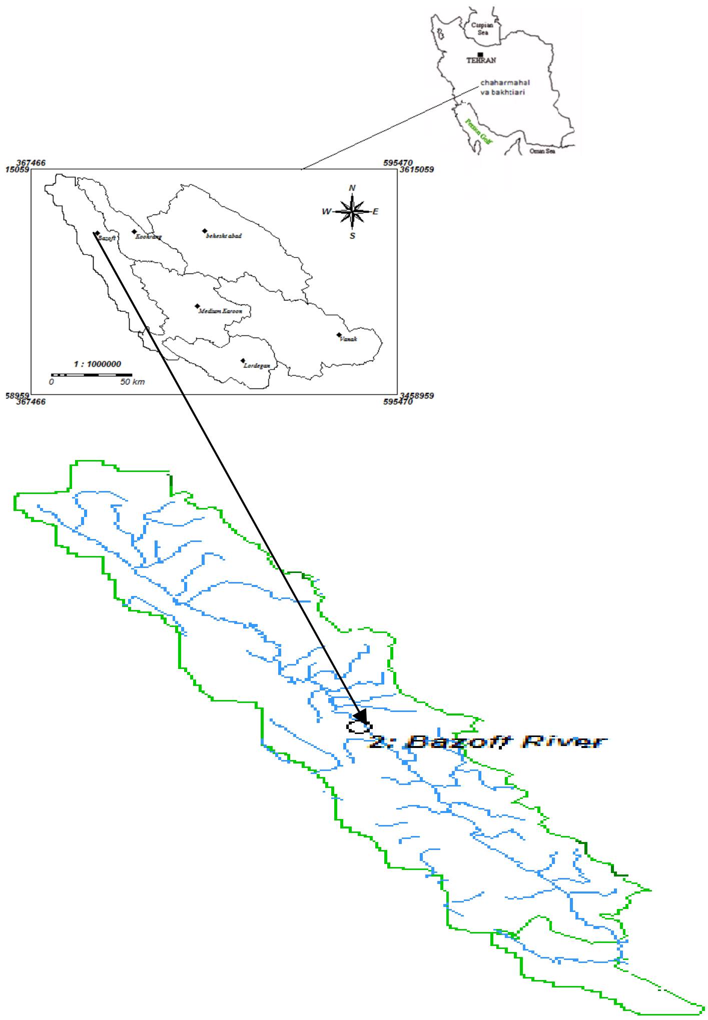


Figure2. Hydrologic location of Bazoft River

2.2 Data sources

Data used in this study are collected from one of the smallest rivers in Iran. The river data include the data from Bazoft. The river under study is categorized as a small river with aspect ratio smaller than 5. Flow depths ranges between 0.39-0.71 m with flow ranging between 5.11 to 49.55 m^3/s. Width of the river ranges between 0.68 to 44.98 m. Average flow velocities of 0.27 to 1.53 m/s were observed. The suspended sediment load ranges between 0.6089 kg/s to as high as 54.0637 kg/s. A summary of the data is given in Table 1. All the 171 sets of data were used in the evaluations of suspended sediment load equations.

Table1: Summary of river data

Data source	Flow discharges (m^3/s)	Flow velocity(m/s)	Flow depth(m)	Width (m)	Surface slope(m)	Suspended sediment Concentration
Bazoft	5.11-49.55	0.27-1.53	0.39-0.71	0.68-44.98	0.0027-0.003	0.6089-54.0637

Data from 1998 to 2009 were collected for validation and also calibration of the formula.

Comparison of estimation results

A very hard and difficult task with MLP is choosing the number of nodes in each of the layers. There is no theory yet to determine that how many hidden units must be considered for each function. In this study, the three layer MLP is used and common trial and error method is used to select the number of nodes, specially the hidden nodes. The input data were normalized before being entered to the model. The river flow discharge was standardized by using standardized option in model. The sediment concentration data were also normalized in a same way. After training was over, the weights were saved and used to test data for each neural network and also models. RMSE and r^2 are denoted as: The comparison between simulated and observed data was evaluated statistically.

Table 2: Performance of MLP as a neural network

Network Type	Decoration	RMSE	R^2
W Q_w	(2 3 1)	0.0457	0.9037
W Q_w V	(3 1 1)	0.0456	0.9040
W Q_w V A	(4 2 1)	0.0462	0.9027
W Q_w V A D	(5 1 1)	0.0461	0.9029
W Q_w V A D RH	(6 2 1)	0.0467	0.9016
W Q_w V A D RH S	(7 3 1)	0.0464	0.9023
Q_w V	(2 1 1)	0.0464	0.9023
Q_w V A	(3 2 1)	0.0464	0.9023
Q_w V A D	(4 2 1)	0.0465	0.9021
Q_w V A D RH	(5 2 1)	0.0463	0.9025
Q_w V A D RH S	(6 4 1)	0.0468	0.9014
V A	(2 1 1)	0.0463	0.9025
V A D	(3 1 1)	0.0464	0.9023
V A W	(3 4 1)	0.0464	0.9023
V A D RH	(4 2 1)	0.0463	0.9025
V A D RH S	(5 3 1)	0.0468	0.9014
A Qw	(2 3 1)	0.0454	0.9044
A D	(2 1 1)	0.0464	0.9023
A W	(3 2 1)	0.0466	0.9018
A D RH	(4 3 1)	0.0464	0.9023
A D RH S	(2 1 1)	0.0465	0.9021
D RH	(2 1 1)	0.0465	0.9021
RH S	(3 2 1)	0.0464	0.9023
D W	(2 3 1)	0.0464	0.9023
D S	(2 2 1)	0.0465	0.9021
D Qw	(2 3 1)	0.0464	0.9023
D RH S	(2 3 1)	0.0462	0.9027

The neuron in the output layer represents suspended sediment flux (Fig. 2). The number of neurons in the hidden layers was decided by a trial-and-error method. Neurons in the input layer represent input variables. Inthis study, twenty seven input combinations, which fell in fourgroups, were used (Table 2). The networks in differentgroups were designed to compare the performances ofdifferent sets of causal variables; while those in the samegroup were designed to examine the degree of number of the parameters effectbetween the inputs and the outputs. The network in group one used the width of the river beside other parameters in each sub group. In this group the second sub group with three input parameters has the best simulation in comparison with others. Among all of the simulations in table 2, it can be recognized that in the third group, the first sub group has the most ability in simulating the flux as an output. In addition individuals were tested, and it was seen that Q_w lonely has more ability than this sub group to predict Q_s. Evaluation of this simulation showed that water discharge can simulate the sediment discharge with RMSE error equal with 0.0315 and also determination coefficient error equal with 0.9667.During the training process the best results were determined in the 535th epoch.

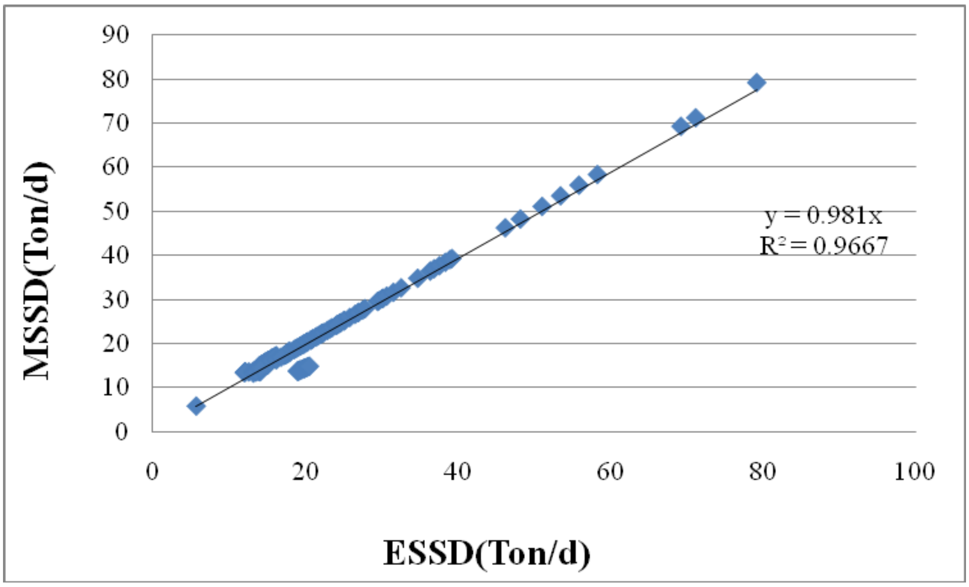


Figure3. Performance of neural network (MLP) in estimation the suspended sediment

Bagnold formula

Suspension

The finer particles of the sediment load of streams move predominantly as suspended load.

Suspension as a mode of transport is opposite to what Bagnold called "surface creep" and to what he defines as the heavy concentration of motion immediately at the bed. In popular parlance this has been called bed load, although as defined in this publication bed load includes only those grain sizes of the surface creep which occur in significant amounts in the bed.

Bagnold (1963, 1966) derived a stream-based sediment transport model. In that model, Bagnold assumes the sediment is transported in two modes, i.e., the bedload transport andthe suspended transport. The bed load sediment is transported by the flow via grain to graininteractions; the suspended sediment transport is supported by fluid flow through turbulentdiffusion. The suspended sediment rate can be calculated using the below formula (Bagnold, 1966)

(3)

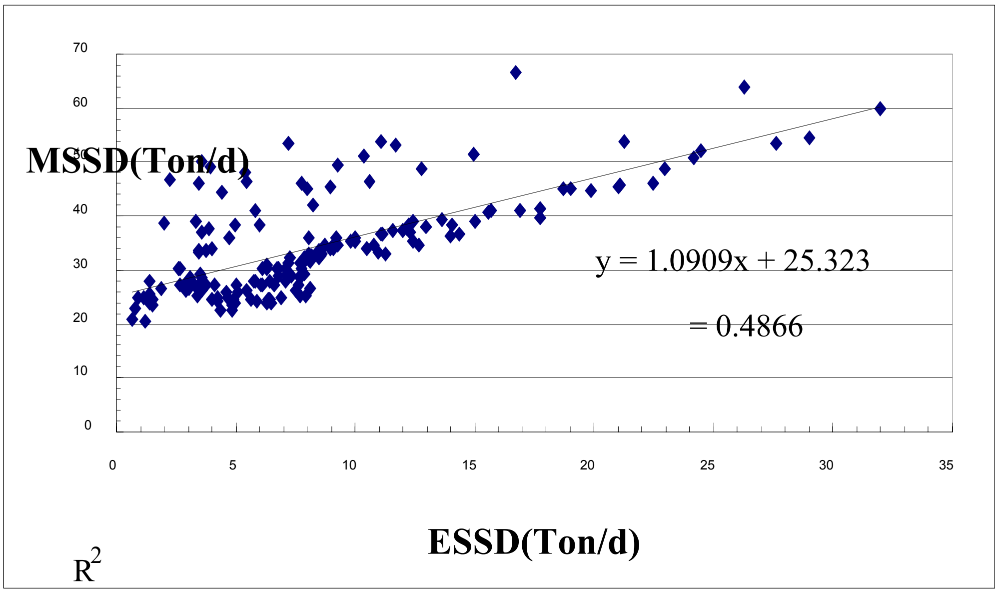
$$g(S_g - 1)q_{sm} = 0.01\tau(\bar{u}^2 / \omega_s)$$

Where ω_s, is the fall velocity of sediment, S_g is assumed as the ratio of water density by sediment density. $\bar{u}$ is the mean velocity, τ is the shear stress and at last q_{sm} is the sediment discharge.

The performance of Bagnold to estimate the suspended sediment is evaluated using RMSE and R^2. Table 3 shows that Bagnold with five input parameters cannot estimate the suspended load accurately. The input parameters of this formula are both morphological and hydrological but in comparison with the first group (the second sub group) and the third group (the first sub group) of neural network, it cannot estimate the suspended sediment flux as well.

Table3. Evaluation of Bagnold formula performance

Input parameters	Out put	Observed Annual Mean suspended sediment discharge	Estimated Annual Mean suspended sediment discharge	RMSE	R^2
S_g, τ, $\bar{u}$, g, ω_s	q_{sm}	78.93	21.56	0.069	0.72



MSSD: is the measured suspended sediment discharge
ESSD: is the estimated suspended sediment discharge

Figure 3: performance of Bagnold in estimation of suspended sediment discharge

The performances evaluation showed clearly in Figure3that the Bagnold method using shear stress, water and sediment density, mean velocity of water and also fall velocityas input variables performs poor than the artificial neural networks. The Bagnold method cannot estimate the nonlinear suspended sediment flux with high accuracy, due to their simple structure and mathematical methods. Kisi (2004) demonstrated the evidence of ANN ability in Daily River suspended sediment concentration modeling. According to Brikundavyi*et al.* (2002), the performance of the BP was found to be superior to conventional statistical and stochastic methods in continuous flow series forecasting. The superiority of artificial neural networks over a conventional method in the reviewed prediction study can be attributed to their capability to capture the nonlinear dynamics and generalize the structure of the whole data set (Celikoglu and Cigizoglu, 2007).Obviously, using the artificial neural networks for modeling sediment estimation is more reliable than the Bagnold method in the weir studied herein.

3. Conclusion

A study on the suspended sediment discharge on river with aspect ratio smaller than 5 was conducted. From the evaluations on the selected transport equation and neural network, neural network and using MLP as the type of network gave good performance when tested against field data in comparison with Bagnold method. In this study the artificial neural networks methodologies were applied to estimate the weir daily-based suspended sediment discharge by using morphological and hydrological parameters as input variables. From the results of this study, the BP configuration established shows the highest statistical performance in the sediment estimation when the water discharge data was used as input variables in the network. ANN can generate a better fit to the observed suspended sediment flux when an individual water discharge is used as the input parameter. It was demonstrated that using area of the cross section of the river and water discharge in association as the input variables can create a good simulation but in comparison with using individual parameter like water discharge the simulation would be worse. The results of the evaluations showed that both neural network and Bagnold cannot be introduced as accurate models for suspended sediment estimation so further studies needed to develop a model that can estimate the suspended sediment discharge up to its importance accurately.

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