ESTIMATION OF SEDIMENT CONCENTRATION IN RIVERS BY USING NEURAL NETWORKS

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Artificial neural network is an advanced topic which provides hydraulic and environmental engineers with a strong tool for estimating missing information to be used for design purposes and management practice. In this study, a neural network is used to estimate the natural sediment discharge in rivers in terms of sediment concentration. This is achieved by training the network to extrapolate data collected from reliable sources. Selecting an appropriate neural network structure and a training algorithm as well as providing data to the network are addressed using a constructive algorithm called back-propagation algorithm (BPA). Sensitivity analysis is performed for flow and sediment parameters. The predicted sediment concentrations are agreed well with the measured ones.

Key Words : *Sediment transport, natural rivers, neural networks, back propagation algorithm*

1. INTRODUCTION

Dynamics of sediments in streams and rivers is a complex process and it depends on variety of variables and parameters. Several approaches have been presented to estimate sediment discharge by using similarity principle[1)], dimensional analysis[2)], analytic power models[3)], and etc. To get a discrete formula to be used, some effective parameters should be disregarded, and the accuracy of the predicted results will decrease. Recently, neural networks have been applied to many applications in science. The technique is not deeply examined yet for fluvial engineering and sediment transport. This paper evaluates the applicability of neural networks approach on sediment transport and environmental problems using the back propagation algorithm[4)].

Several trials are done to decide the effective input parameters and to design the suitable architecture of the network. Results showed that neural networks approach is providing a good prediction compared to conventional models.

2. NEURAL NETWORKS MODEL

(1) The network architecture

Artificial neural network (ANN) is a net of simple units, each possibly having a local memory.

Units are connected by unidirectional links, which carry numeric data. The semilinear feed forward net[4)] has been found to be effective system for learning discriminates for patterns from a body of examples. Outputs of nodes in one layer are transmitted to nodes in another layer through links that amplify or inhibit such outputs through weighting factors. Except for the input layer nodes, the net input to each node is the sum of weighted outputs of the nodes in the prior layer. Each node is activated in accordance with the input to the node, the activation function of the node, and the bias of the node. **Figure 1** shows the general feed-forward multilayer net, including hidden layer. The input pattern constitutes the inputs to the nodes in layer i representing a set of variables ($x_1,x_2,...,x_n$). Outputs of nodes in that layer may be taken equal to inputs, or inputs can be normalized to be scaled to fall between the values of 0 and +1. Output layer generally consists of multiple nodes ($o_1,o_2, ...o_j$), sometimes, it has a single variable o. A node, **Fig. 2**, simulated neuron, is the basic block of the network.

The node sums the product of inputs and connection weights from nodes of previous layer and then limits it by nonlinear threshold function.

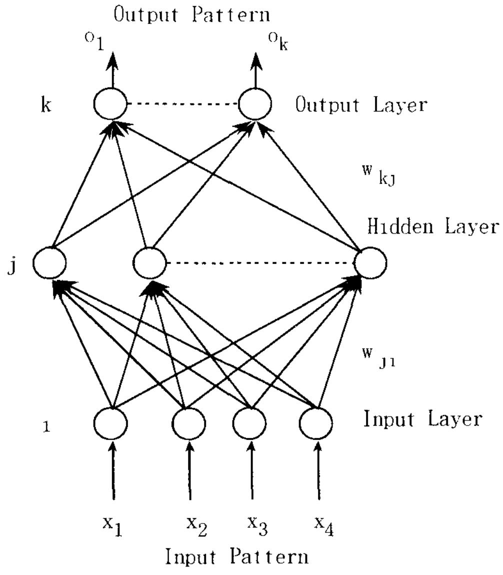

Fig. 1 Feed-forward multilayer network.

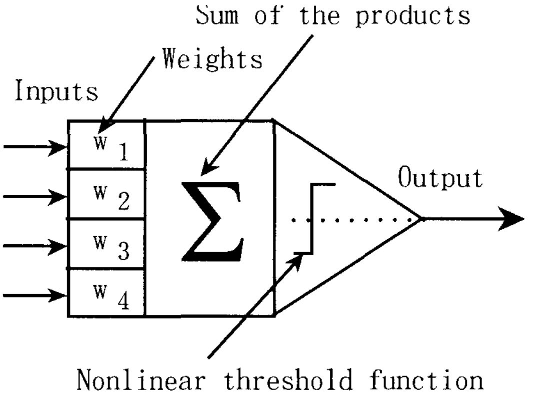

Fig. 2 Functional model of node simulated neuron.

The net input and output to the j'th node are

$$net_j = \sum_i w_{ji} o_i \qquad (1)$$

$$o_j = f(net_j) \qquad (2)$$

where f is the activation function. In calculating the output of a node, activation function may be in the form of a threshold function, in which output of node is generated if a threshold level is reached.

(2) General delta rule (GDR)

In the learning phase of training such a net, the pattern x_p is presented as input, where p is pattern number. The net is asked to adjust the set of weights in all connecting links. Once this adjustment has been accomplished, another pair of x_p and t_{pk} is presented, and ask that the net learn that association too. In general, actual outputs o_{pk} will not be the same as the target or desired value t_{pk}. For each pattern, square of average error is

$$E_p = \frac{1}{2} \sum_k (t_{pk} - o_{pk})^2 \qquad (3)$$

The derivative of the error function E with respect to any weight in the network is in proportional to the incremental change of weights.

For general delta rule, the change of weight for the pair from j'th to i'th nodes can be set as

$$\Delta w_{ji} = - \frac{\partial E}{\partial w_{ji}} = \varepsilon \delta_j o_i \qquad (4)$$

where $\delta_j = -\partial E/\partial o_j f'(net_j)$, ε is the learning rate, and $f'(net_j) = \partial o_j / \partial net_j$.

The deltas at internal node can be evaluated in terms of the deltas at an upper layer. In particular, the o_j is represented by a sigmoid function[5],

$$o_j = \frac{1}{1 + \exp[-\alpha(\sum_i w_{ji} o_i - \theta_j)]} \qquad (5)$$

where α is the shaping ratio of function f, and θ_j serves as a threshold or bias. Then, the following expressions may be presented, for output and hidden layers, respectively.

$$\delta_{pk} = (t_{pk} - o_{pk})\, o_{pk}\, (1 - o_{pk})\, \alpha \qquad (6)$$

$$\delta_{pj} = o_{pj}(1 - o_{pj})\, \alpha \sum_k \delta_{pk} w_{kj} \qquad (7)$$

(3) Back-propagation algorithm

Using the back-propagation procedure, the net calculates $\Delta_p w_{ji}$ for all the w_{ji} in the net for that particular p. This procedure is repeated for all the patterns in the training set to yield the resulting Δw_{ji} for all the weights for that one presentation.

The correction to the weights are made and the output(s) are again evaluated in feed-forward manner. Discrepancies between actual and target output values again result in evaluation of weight changes. After complete presentation of the all patterns in the training set, a new set of weights is obtained and new outputs are again evaluated in feed-forward manner. This is repeated until a specific tolerance for error is obtained.

3. ESTIMATION OF SEDIMENT DISCHARGE

The pertinent variables in river hydraulics are the water discharge per unit width, q, water depth, h, longitudinal slope, S, bed shear stress, τ, sediment discharge per unit width, q_t, median diameter, d_{50}, sediment and fluid density, ρ_s and ρ, kinematic viscosity, ν, acceleration gravity, g and fall velocity, w_0. For natural sand, parameters ρ_S and ρ are constants. $C_s = q_t/q$, and τ can be represented in terms of shear velocity, $u_* = \sqrt{ghS}$. These parameters are presented in dimensionless form as,

$$C_s = f\ (\psi, \phi, w_0/u_*, S, h/d_{50}, F_r, R_{e*}, h/B) \quad (8)$$

where $\psi = hS/sd_{50}$ is the dimensionless tractive shear stress, s is the specific gravity = 1.65 for sand, $\phi = u_m/u_*$ is the velocity ratio, u_m is the mean velocity, w_0/u_* is the dimensionless suspended sediment parameter, h/d_{50} is depth scale ratio, $F_r = u_m/\sqrt{gh}$ is the Froude number, $R_{e*} = u_* d_{50}/\nu$ is the shear velocity Reynolds number, and h/B is width scale ratio. The net is set up with the 8 parameters of Eq. 8 as input pattern, and sediment concentration C_S as the output pattern. The network is trained with well shuffled data. Input layer contains 8 neurons, while output layer contains one. Between them, there is another hidden layer contains suitable number of neurons (under investigation).

(1) Data for learning and verification

Measuring total sediment discharge in rivers is difficult in normal conditions. The available data sets for flow and sediments in rivers, which comprise wide range of situations and contain the total load discharge, are those of the Niobrara River[6], the Middle Loup River[7], the Hii River[8], and the small streams[9].

Table 1 Range of used data in learning and verification.

Variables	Range
Tractive shear stress (ψ)	0.10 ~ 3.68
Velocity ratio (ϕ)	4.10 ~ 15.0
Suspension parameter (w_0/u_*)	0.13 ~ 2.39
Longitudinal slope (S)	0.00041 ~ 0.00287
Water depth ratio (h/d_{50})	152 ~ 6242
Froude number (F_r)	0.15 ~ 0.56
Shear vel. Reynolds no. (R_{e*})	4.36 ~ 135.5
Stream width ratio (h/B)	0.002 ~ 0.10
Sediment concentration (C_s)	10 ~ 3240

Other published data are not used in learning to eliminate their uncertainty of unmeasured load near the bed surface. The data are consisting of 161 sets.

Accuracy of data depends on their publishers. Half of the data are used for learning process. The other half are used for verification. Ranges of used variables are summarize in **Table 1.**

(2) Calibration of neural networks parameters

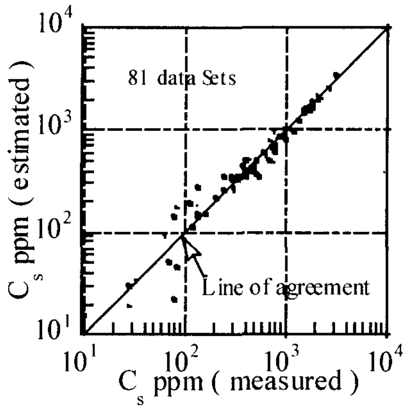

Fig.3 Comparison between measured and estimated concentration,C_s.

The model is constructed with 81 shuffled data sets (patterns). The original target output data are destroyed during learning process. New results are obtained for the 81 data sets. Number of neurons in the hidden layer, the parameters α and ε are determined by calibration through several computer run tests. The parameter ε is recommended to be in the range of (0.04 to 0.10). The best fittings is shown in **Fig. 3**, where number of neurons in the hidden layer is 12, the parameter ε is equal to 0.075, and the parameter α is equal to 12.

Additional 80 patterns are added without target outputs, C_s. Estimated values are obtained. **Fig. 4**, shows the verification between the measured and estimated values for these patterns.

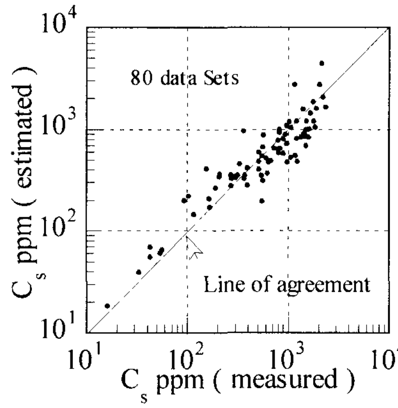

Fig. 4 Verification of the presented model.

4. SENSITIVITY ANALYSIS FOR WATER AND SEDIMENTS PARAMETERS

Several experiments are conducted to examine the sensitivity of the provided sediment parameters in each pattern. With fixed model parameters, the first run is carried out with the 8 input parameters which mentioned above. Then, each parameter is eliminated by turn from the group. A statistical analysis is conducted for determining the accuracy in each case.

Discrepancy ratio $D_r=C_c/C_m$ is used for comparison, where C_c is the calculated total load concentration, and C_m is the measured one. The mean value, $\overline{D_r}$, and the standard deviation, σ, are

$$\overline{D_r} = \sum_{i=1}^{N} D_{ri} \Big/ N, \quad \sigma = \sqrt{\sum_{i=1}^{N} (D_{ri} - \overline{D_r})^2 \Big/ N-1}$$

, respectively. Also, the ranges of ±25%, ±50%, and ±75% of the predicted concentrations are presented.

Table 2 Effect of flow and sediment parameters on results accuracy.

Inputs of flow and sediment parameters	Number of data sets	Discrepancy Ratio				
		Mean	Standard Deviation	Percent of Data in Range		
				0.75~ 1.25	0.5 ~ 1.5	0.25 ~ 1.75
1.The full parameters in Eq. 8	161	1.03	0.40	65	87	94
2. Eliminating " ψ "		1.30	1.45	58	80	87
3. Eliminating " ϕ "		1.01	0.60	60	85	92
4. Eliminating " w_0/U_* "		1.57	2.50	53	78	86
5. Eliminating " S "		1.05	0.56	59	81	89
6. Eliminating " h/d_{50} "		1.85	2.40	55	69	78
7. Eliminating " F_r "		1.29	1.47	58	78	87
8. Eliminating " R_{e*} "		1.20	1.25	63	82	89
9. Eliminating " h/B "		1.03	1.74	42	78	87

From **Table 2**, it can be concluded that the most important dimensionless parameters in the group are ψ, w_0/u_*, h/d,F_r, R_{e*} and h/B. The parameters which have effect less than 10% may be neglected without fear of accuracy, such as, ϕ, and S. The new group of parameters is tested again after eliminating non-effective ones. The functional form of new group is,

$$C_s = f\ (\psi\ , w_0 / u_*\ , h / d_{50}\ , F_r\ , R_{e*}\ , h / B) \qquad (9)$$

5. COMPARISON WITH THE PREVIOUS STUDIES USING TOTAL LOAD DATA

A comparison between the presented model results and seven previous studies[3),15)] is performed. The analysis are shown in **Table 3**. **Figure 5** shows the best fit for results of the presented model and Brownlie formula[2)], which gives better results than others.

Table 3 Accuracy of formulas for total sediment concentration, { field data }.

Method	Number of data sets	Discrepancy Ratio				
		Mean	Standard Deviation	Percent of Data in Range		
				0.75~ 1.25	0.5 ~ 1.5	0.25 ~ 1.75
1. Presented ANN model, Eq. 9	80	1.04	0.42	58	78	93
2. Engelund and Hansen (1967)		2.34	1.69	14	35	45
3. Ackers and White (d_{50}) (1973)		1.10	1.45	48	75	90
4. Yang (d_{50}) (1973)		1.30	0.81	51	69	81
5. Brownlie (1981)		1.04	0.67	56	76	93
6. Shen and Hung (1972)		1.26	0.62	44	70	84
7. Laursen (1958)		0.55	0.89	8	20	60
8. Toffaleti (1968)		0.41	0.46	5	20	66

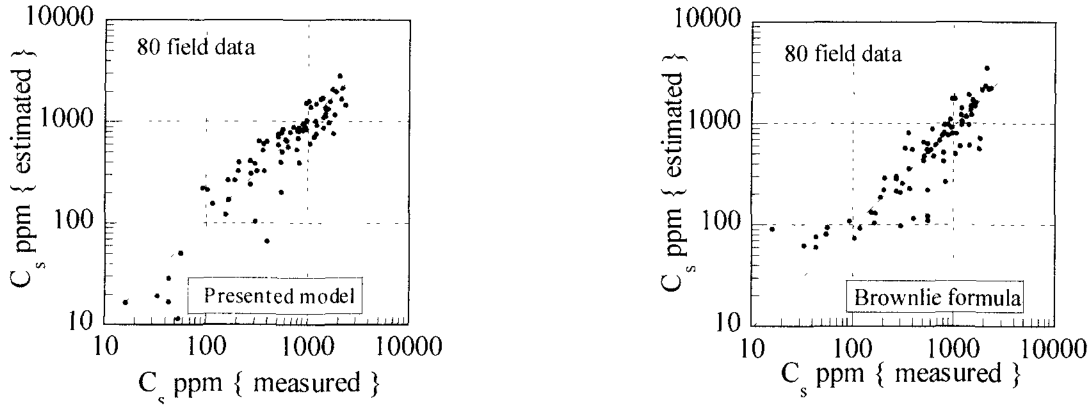

Fig. 5 Comparison between the presented model and Brownlie formula.

6. EVALATION OF THE MODEL USING SUSPENDED SEDIMENT DATA

Another group of 485 data sets are used for verification. Those data were collected from the Rio Grande River[10),11),12)], the Mississipi River[13)], and the Sacramento River[14)]. Their measured sediment discharge represents suspended load. The bed load concentration, C_b still needs to be determined. Meyer-Peter and Muller formula[15)] for bed load is used to calculate the unmeasured part. Thus, total concentration C_s is the summation of measured suspended load concentration C_{sus} and the calculated bed load concentration C_b. The sets which have $C_s<10$ are excluded, see **Table 1**. Range of variables is shown in **Table 4**. The Mississipi and the Sacramento Rivers have some variables with ranges wider than the used trained patterns variables, therefore, their sediment concentration can not be extrapolated. Thus, half of the Mississipi River data are used as a new training patterns to estimate the other half and the Sacramento River sediment concentration. The comparison with other formulas shows that the model gives best results in some rivers, and one of the three best results in others. If the trained patterns contain data with wider range variables, the model accuracy will be the best of all. **Table 5**, shows the error analysis for results in all tested rivers using the ANN model among the best 5 of 10 tested formulas[3),15)] for total sediment discharge. The $\overline{D}_r$ value of Nordin-Beverage group is rather large because most of sets have variables with extremely larger ranges than the trained ones, see **Tables 1** and **4**.

Table 4 Hydraulic and sediment data for the tested rivers.

Variable \ River	Rio Grande (Nordin)	Rio Grande (Nordin &Beverage)	Rio Grande (Culberston)	Mississipi (Jordan)	Sacramento (Nakato)
Num. of data	58	234	139	34	20
ψ	0.29~2.34	0.08~5.98	0.5~4.46	0.29~2.39	0.25~2.98
w_0/u_*	0.28~1.06	0.17~2.79	0.16~0.67	0.17~1.36	0.36~1.58
h/d_{50}	583~4735	107~8388.2	1016~14696	10855~56693	3220~18770
F_n	0.24~0.68	0.11~0.58	0.225~0.79	0.084~0.196	0.11~0.21
R_{e*}	8.29~33.61	5.9~396.54	6.36~32.67	6.29~94.85	18.6~149
h/B	.0017~.042	0.002~0.078	.0014~.066	0.01~0.031	0.017~.078
C_s total	130~4236	10~9186	285~6773	13~271	23~242
C_b/C_s %	15%	31%	11%	9.25%	30%

Table 5 Accuracy of methods for different rivers data.

Rio Grande River data (by Nordin).

Method	Number of data sets	Discrepancy Ratio				
		Mean	Standard deviation	Percent of Data in Range		
				0.75~ 1.25	0.5 ~ 1.5	0.25 ~ 1.75
1. Presented ANN model, Eq. 9		0.998	0.46	41	76	88
2. Engelund and Hansen (1967)		0.96	0.44	37	72	91
3. Ackers and White (d_{50}) (1973)		0.80	0.48	33	71	84
4. Yang (d_{50}) (1973)	58	0.57	0.25	26	66	88
5. Brownlie (1981)		0.88	0.48	31	69	85
6. Shen and Hung (1972)		0.74	0.41	31	62	86

Rio Grande River data (by Nordin and Beverage).						
1. Presented ANN model, Eq. 9	234	1.55	6.0	31	67	84
2. Engelund and Hansen (1967)	234	2.9	8.3	31	39	54
3. Ackers and White (d_{50}) (1973)	233	0.96	0.8	33	62	82
4. Yang (d_{50}) (1973)	233	1.37	1.40	35	56	77
5. Brownlie (1981)	234	1.53	1.15	35	64	84
6. Shen and Hung (1972)	234	1.21	0.91	36	62	79
Rio Grande River data (by Culberston and Dawdy).						
1. Presented ANN model, Eq. 9		0.93	0.43	45	76	92
2. Engelund and Hansen (1967)		0.95	0.43	46	75	93
3. Ackers and White (d_{50}) (1973)		1.37	0.74	32	57	75
4. Yang (d_{50}) (1973)		0.62	0.28	24	68	93
5. Brownlie (1981)	139	1.21	0.56	37	67	84
6. Shen and Hung (1972)		0.95	0.44	45	77	93
Sacramento River data (by Nakato).						
1. Presented ANN model, Eq. 9		1.01	0.43	40	85	95
2. Engelund and Hansen (1967)		2.48	2.01	10	30	40
3. Ackers and White (d_{50}) (1973)		1.0	0.76	35	55	75
4. Yang (d_{50}) (1973)	20	1.08	0.75	45	75	80
5. Brownlie (1981)		1.62	1.31	35	70	75
6. Shen and Hung (1972)		1.23	1.46	40	55	70
Mississppi River data (by Jordan).						
1. Presented ANN model, Eq. 9		0.98	0.33	53	88	100
2. Engelund and Hansen (1967)		1.68	0.90	35	44	59
3. Ackers and White (d_{50}) (1973)		1.09	0.70	35	50	82
4. Yang (d_{50}) (1973)		0.75	0.50	35	50	88
5. Brownlie (1981)	34	1.40	0.59	29	56	68
6. Shen and Hung (1972)		0.59	0.43	15	53	76

7. CONCLUSIONS

The present study illustrates one particular aspect of hydroinformatics as an application on sediment transport problems. Knowing the data record for sediments in some station on rivers, allows us for estimating the amount of transported sediment in the same river or in another one. The neural networks model can be successfully applied for the sediment transport when other approaches can not succeed with the uncertainty and the stochastic nature of the sediment movement. Increasing input patterns for learning with wide range variables, which come from well established database system, will increase the accuracy of the model estimated values.

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