SEDIMENT TRANSPORT CAPACITY IN OPEN CHANNELS: NEURAL NETWORKS APPROACH

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ABSTRACT

Artificial neural networks 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 networks 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 networks 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 agreed well with the measured ones.

Keywords: Sediment transport, natural rivers, neural networks, back propagation algorithm.

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, Engelund-Hansen [1], dimensional analysis, Brownlie [2], or analytic power models, Yang [3], among others. A simple look on those previous approaches, it is recognized that the presented relations are nonlinear in form. In order to get a discrete formula to be used, some effective parameters should be disregarded, and of course the accuracy of the predicted results will decrease. Moreover, it is well known that the incipient motion of sediment particles in alluvial streams is probabilistic in nature. Thus, equations with concrete form for sediment discharge can not provide accurate estimates.

Recently, neural network as a technique has been successfully applied to many applications in civil engineering; structural engineering, hydrology and flood discharges, as well as in many other fields. As far as the writer knows, the technique is not deeply examined yet for fluvial engineering and sediment transport. This paper evaluates the applicability of neural network approach on sediment transport and environmental problems using the back-propagation algorithm developed by Rumelhart, et. al.[4]. Several trials are done to decide the effective input parameters and to design the suitable architecture of the network. The results showed that the neural network approach is providing a good prediction compared to the conventional models. Also, the results showed that the neural network approach may not require omitting variables or smoothing on the data set. The model can

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be applied to estimate contaminant sediment quantities in natural streams in case of existence of contaminant sources.

ARTIFICIAL NEURAL NETWORK MODEL

The Network Architecture

An artificial neural network (ANN) is a processing device, either an algorithm, or actual hardware, whose design was motivated by the design and functioning of human brains and components thereof. It is a net of many simple processors, units, each possibly having a local memory. The units are connected by unidirectional communication channels, connections, which carry numeric data. The units operate only on their local data and on the inputs they receive via the connections. Most neural networks have some sort of training rule whereby the weights of connections are adjusted on basis of presented patterns.

The semilinear feed forward net as reported by Rumelhart, *et al.* [4] has been found to be effective system for learning discriminates for patterns from a body of examples. In general, such a net is made up of sets of nodes arranged in layers. The 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 the 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 a general feed-forward multilayer ANN, including a hidden layer.

The components of an input pattern constitute the inputs to the nodes in layer i representing a set of variables ($x_1, x_2, \ldots, x_n$). Outputs of nodes in that layer may be taken equal to inputs, or inputs can be normalized in the sense to be scaled to fall between the values of 0 and +1.

The output layer generally consists of multiple nodes ($o_1, o_2, \ldots, o_j$), sometimes, it has a single variable o. A node, shown in Figure 2, simulated neuron, is the basic building block of the network. The node sums the product of the inputs and the connection weights from the nodes of the previous layer and then limits it by a nonlinear threshold function.

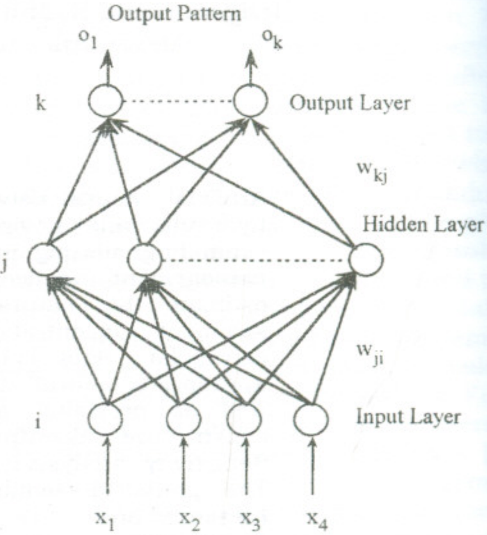

Figure 1 Feed-forward multilayer network

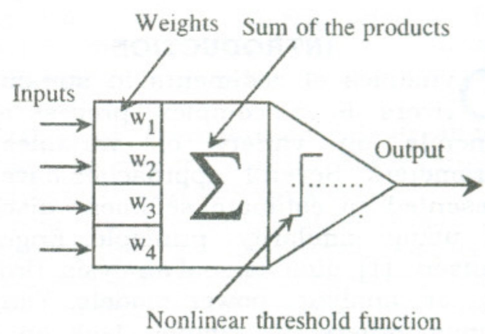

Figure 2 Functional model of a node simulated neuron

The net input to the j'th node is

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

The net output of the j'th node is given by

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

where f is the activation function. In calculating the output of the node, activation function may be in the form of a threshold function, in which the output of the node is generated if a threshold level is reached. The sigmoidal activation function, see [5], is presented as follows,

$$o_j = \frac{1}{1 + e^{-\alpha(net_j + \theta_j)}} \qquad (3)$$

where α is the shaping ratio of function f, and the parameter θj serves as a threshold or bias. Positive θj is to shift the activation function to the left along the horizontal axis, or modify the shape of sigmoid function, (Adjustment of this value can speed up convergence during learning). Similarly,

$$net_k = \sum w_{kj} \; o_j \qquad (4)$$

where net_k is the input to the k'th node and by definition is the weighted linear sum of all the outputs from the previous layer. The corresponding outputs

$$o_k = f(net_k) \qquad (5)$$

General Delta Rule (GDR)

In the learning phase of training such a net, the pattern x_p is presented as input, therefore, the net is asked to adjust the set of weights in all the connecting links and also all the thresholds in the nodes such that the desired outputs t_{pk} are obtained at the output nodes. Once the net has accomplished this adjustment, another pair of x_p and t_{pk} is presented, and ask that the net learn that association too. In general, the actual outputs o_{pk} will not be the same as the target or desired (target) value t_{pk} . For each pattern, the square of error is

$$E_p = \frac{1}{2} \sum_k (t_{pk} - o_{pk})^2 \qquad (6)$$

and the average system error, with omitting the p subscript for conveniences, is

$$E = \frac{1}{2} \sum_k (t_k - o_k)^2 \qquad (7)$$

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 generalization of the General Delta Rule (GDR), the weight change for the pair from j'th to k'th nodes can be set as

$$\Delta w_{kj} = -\varepsilon \frac{\partial E}{\partial w_{kj}} \qquad (8)$$

where ε is the learning rate. The error E, may be expressed in terms of outputs o_k, which is the nonlinear output of the node k, as presented in Equation 5. The partial derivative $\partial E/\partial w_{kj}$ can be evaluated using the chain rule, and Equation 4, thus

$$\Delta w_{kj} = \varepsilon \, \delta_k \, o_j \qquad (9)$$

where

$$\delta_k = -\frac{\partial E}{\partial net_k} \qquad (10)$$

Again, using chain rule for δ_k , and get the derivative of Equation 7, yields for output-layer node k,

$$\Delta w_{kj} = \varepsilon \, (t_k - o_k) \, f_k'(net_k) \, o_j \qquad (11)$$

where $f_k'(net_k) = \partial o_k / \partial net_k$ and then,

$$\delta_k = (t_k - o_k) \, f_k'(net_k) \qquad (12)$$

In case of using one hidden layer or multi-layers, weights do not affect output nodes directly.
Symbols i, j , k will represent input, hidden, and output layer, respectively. Thus,

$$\Delta w_{ji} = -\frac{\partial E}{\partial w_{ji}} = \varepsilon \delta_j o_i \qquad (13)$$

where $\delta_j = -\partial E/\partial o_j f'(net_j)$. However, the factor $-\partial E/\partial o_j$ cannot be evaluated directly. Thus it may be presented in other quantities that can be evaluated,

$$-\frac{\partial E}{\partial o_j} = -\sum_k \frac{\partial E}{\partial net_k}\frac{\partial net_k}{\partial o_j} = \sum_k \left(-\frac{\partial E}{\partial net_k}\right)\frac{\partial}{\partial o_j}\sum_j w_{kj} o_j$$

$$= \sum_k \left(-\frac{\partial E}{\partial net_k}\right) w_{kj} = \sum_k \delta_k \, w_{kj} \qquad (14)$$

Thus,

$$\delta_j = f'(net_j) \sum_k \delta_k w_{kj} \quad (15)$$

That is, the deltas at an internal node can be evaluated in terms of the deltas at an upper layer. Summarizing, and using the additional subscript p to denote the pattern number,

$$\Delta_p w_{ji} = \varepsilon \delta_{pj} o_{pi} \quad (16)$$

If the j nodes are output-layer nodes,

$$\delta_{pj} = (t_{pj} - o_{pj}) f_j'(net_{pj}) \quad (17)$$

However, if the j'th nodes are internal nodes, then we need to evaluate δ_{pj} in terms of δ's at a higher layer; that is,

$$\delta_{pj} = f_j'(net_{pj}) \sum_k \delta_{pk} w_{kj} \quad (18)$$

In particular, if the o_j is represented by a sigmoidal function, see[4],

$$o_j = \frac{1}{1+\exp[-\alpha(\sum_i w_{ji} o_i + \theta_j)]} \quad (19)$$

then

$$\frac{\delta o_j}{\delta net_j} = o_j (1 - o_j) \alpha \quad (20)$$

Then Equations 12 and 18 may be modified by the following two expressions :

$$\delta_{pk} = (t_{pk} - o_{pk}) o_{pk} (1 - o_{pk}) \alpha \quad (21)$$

$$\delta_{pj} = o_{pj}(1 - o_{pj}) \alpha \sum_k \delta_{pk} w_{kj} \quad (22)$$

for the output-layer and hidden-layer units, respectively.

Back-Propagation Algorithm

The learning procedure consists of the net starting off with a random set of weight value, choosing one of the training-set patterns, and, using that pattern as input, evaluating the output(s) in a feed-forward manner. The errors at the output(s) generally will be quite large, which necessitates changes in the weights. 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 all patterns in the training set, a new set of weights is obtained and new outputs are again evaluated in feed-forward manner. The net can be made to track the system error and also the errors for individual patterns. In a successful learning exercise, system error will decrease with the number of iterations, and the procedure will converge to a stable set of weights, which exhibit only small fluctuation in value as further learning is attempted. This is called "back-propagation" because the computation of the δ's implemented by propagation error signals backward through the network.

DETERMINATION OF SEDIMENT DISCHARGE

The artificial neural network seems the appropriate approach to predict the sediment discharge in terms of sediment concentration Cs (ppm) using all the basic parameters of fluvial hydraulics. The pertinent variables of river hydraulics are water discharge per unit width q, flow velocity u, water depth h, total energy slope S, bed shear stress g, sediment discharge per unit width qt, median sediment diameter d50, geometric standard deviation σ_g, sediment and fluid density ρs and ρ, fluid kinematics viscosity ν, acceleration of gravity g, sediment shape factor SF, temperature T, river width B. The idea here is to use only measured data, not calculated by any type of equations, and avoid of using dimensional analysis to create dimensionless parameters. In case of natural sand, the parameters ρ_s and ρ can be considered constants, also the acceleration of gravity g is constant. The parameter of bed shear stress can be represented in terms of shear velocity u_o, and the parameter C_s will represent the value of q_t/q. Sensitivity analysis is performed using the model for all available parameters (not published here to conserve space). Non-effective parameters on model results are avoided. As a result, the most general possible form for sediment transport function is:

$$C_S = \varphi\,(d_{50}, u, u_*, \nu, S, h) \qquad (23)$$

The network Fortran program is set up with the six parameters d_{50}, u, u_*, ν, S and h as input pattern, and with the sediment concentration C_S in ppm as the output. The network was trained with will shuffled data using one hidden layer contains suitable number of neurons (under investigation). The input layer contains 7 neurons, while the output layer contains one neuron. The number of trained patterns are 200 data sets, while the number of predicted ones are 50 patterns.

Laboratory Data Used for Learning

The most trusting published data for flow and sediments which comprise a wide range of situations, are those the experimental data which was collected by Guy *et al.* [6]. The data are consisting of 10 different groups. The tests were performed in two different recirculating flumes; the larger one was 8 ft (2.44 m) wide, 2 ft (0.61 m) deep and 150 ft (45.72 m) long, the smaller one was 2 ft (0.61 m) wide, 2.5 ft (0.76m) deep and 60 ft (18.29 m) long. The ranges of variables which used are summarized in the Table 1.

Table 1 Range of experimental data used for learning

Flow variables	Range	Sediment variables	Range
Velocity V (m/sec)	0.396 ~ 1.93	Particle size d_m (mm)	0.19~0.93
Long. slope S	0.00015 ~ 0.0193	Standard Deviation σ_g	1.25~2.07
Water depth h (m)	0.058 ~ 0.405	Sediment Conc. C_S (ppm)	100~ 50000
Temperature T (°C)	7 ~ 34.7		
Kin. Viscosity ν (cm^2/sec)	0.0073 ~ 0.0297		
Shear velocity u_* (m/sec)	0.02 ~ 0.198		
Froude Number F_r	0.14 ~ 1.7		

Calibration of the network parameters

The number of neurons in hidden layer, the α and ε coefficients were determined by calibration between actual and estimated data through several computer run tests. In Figure 3, number of neurons in the hidden layer is used as a variable through a verification graph for measured and calculated data. Figure 4 shows the effect of changing the coefficient on the accuracy of predicted results. The difference is clear for small values of sediment concentration.

Figure 5 shows the effect of α on the number of iteration and the experimental time. The parameter ε is recommended to be in the range of (0.04 to 0.15).The best fittings between measured and predicted data for sediment concentration is shown in Figure 6, where the number of neurons in the hidden layer =12, ε= 0.04, and α= 4. The mean value of the discrepancy ratio, C_c/C_m, is 1.08, and the standard error of the mean is 0.051.

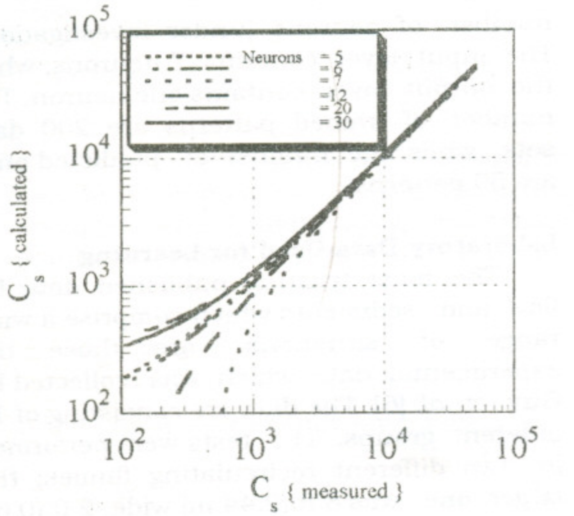

Figure 3 Effect number of neurons on the accuracy of results.

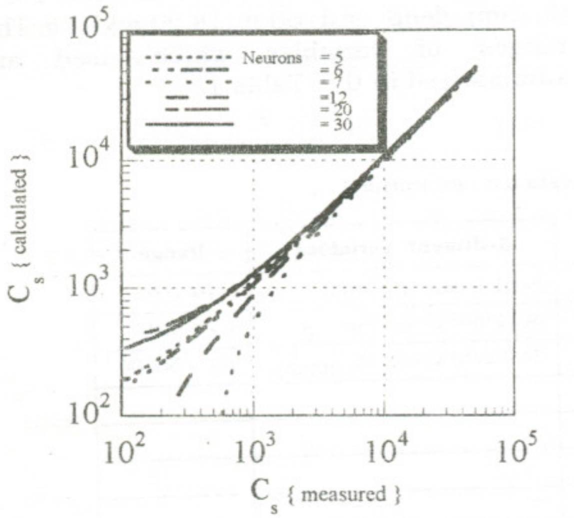

Figure 4 Effect of coefficient on the accuracy of results.

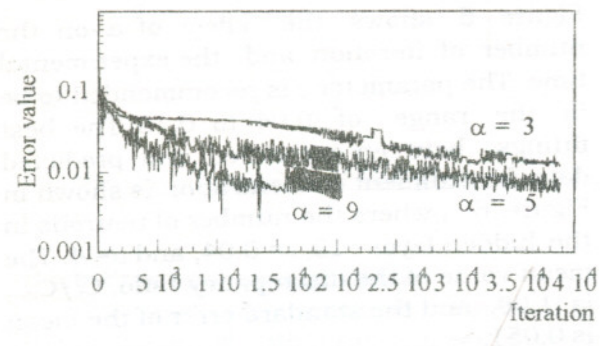

Figure 5 Effect of changing on iteration number and experimental time.

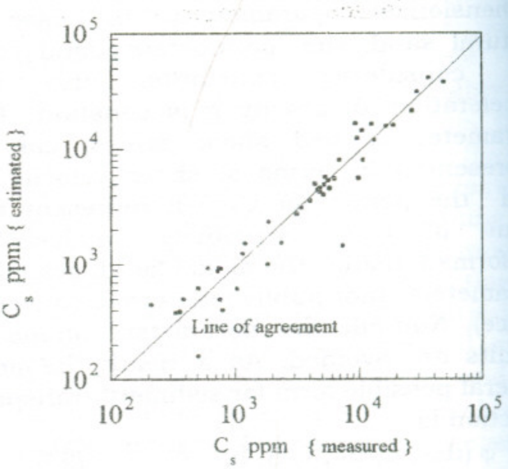

Figure 6 Calibration of the presented ANN model using Guy, et al. [6] experimental data.

Verification of Model

For the purpose of verifying the present analysis for total sediment concentration, the model is checked by using several independent data sets which are not used in the derivation. The data sets which are used in this verification have been selected from previous experimental works and from natural rivers observations. A pool of laboratory data representing 558 experimental run, is prepared from different reliable sources. Among of them, Guy, Simons, and Richardson [6], Williams [7], Williams [8], Taylor [9], Barton and Lin [10], Brooks [11], and Einstein [12]. The data sets contain the measured total concentration of sediments in clear and direct representation. Thus, uncertainty of unmeasured load is avoided. The data were shuffled at random. Two hundred data set were used for training the program. Total load concentrations of the other 358 data sets were predicted by the model. Discrepancy ratio analysis is used for comparison between the results of presented model and the most recent and famous traditional methods presented by others. Discrepancy ratio = $D_r = C_c / C_m$, where C_c is the calculated total load concentration, and C_m is the measured total load concentration. The mean value $\overline{D}_r$ and standard deviation are defined as

$$\overline{D}_r = \sum_{i=1}^{N} D_{ri} \Big/ N \quad \text{and}$$

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

Also, percentages of data that can be found in the ranges of ±25%, ±50%, and ±75% of the predicted concentrations from every method are presented. Ranges of experimental data variables which are used for verification are shown in Table 2. The summary of comparison is presented in Table 3. Figures 7 and 8 show a comparison between the presented model best fit agreement for laboratory data and Brownlie's [2[equation, which gives better results than others.

Table 2 Range of experimental data used for verification

Flow variables	Range	Sediment variables	Range
Velocity V (m/sec)	0.24 ~ 2.34	Particle size d_m (mm)	0.088 ~ 1.35
Long. slope S	4.5 e-05 ~ 0.0367	Sediment Conc. C_s (ppm)	101 ~ 43790
Water depth h (m)	0.024 ~ 1.54		
Temperature T (°C)	7 ~ 34.7		
Kin. Viscosity (cm_2/sec)	0.0073 ~ 0.0297		
Shear velocity u_* (m/sec)	0.022 ~ 0.35		
Froude Number F_r	0.14 ~ 1.7		

Table 3 Accuracy of formulas for total sediment discharge, { Experimental 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
Engelund and Hansen [1]	358	1.98	1.90	31	56	63
Ackers and White(d_{50}) [13]		3.18	4.35	17	35	51
Ackers and White(d_{35}) [13]		3.47	4.66	15	33	46
Yang (d_{50}) [3]		2.25	1.94	25	45	56
Brownlie [2]		0.95	0.67	31	62	84
Shen and Hung [14]		2.09	1.91	28	46	60
Graf [15]		2.72	6.31	27	48	65
Inglis-Lacey [16]		5.65	7.12	8	11	19
Laursen [17]		1.20	0.93	25	51	74
Toffaleti [18]		3.27	6.64	24	54	71
The Presented Model		1.23	0.76	48	76	87

Results obtained for experimental data are encouraging for applying the technique on canals and natural rivers data. A group of 280 sets of rivers data are used for verification. These data were collected from the Mississippi River [19], the Rio-Grande River [20], the Middle Loup River [21], Hii River [22], and small streams [23]. Due to scale effect and the different nature of rivers, the model is applied on each river data set in separate. Half of data sets are used for training the model, while the other half for prediction of sediment concentration. Table 4 summarizes water and sediment data. Summary of the comparison between the present approach and the previous studied for rivers data are presented in Table 5. Figures 9 and 10, show a comparison between the presented model best fit agreement for field data and Yang's [3] equation, which gives better results than others.

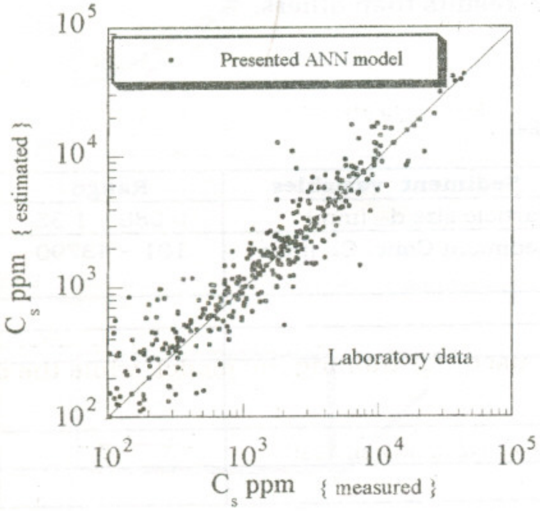

Figure 7 Verification of the present model using data

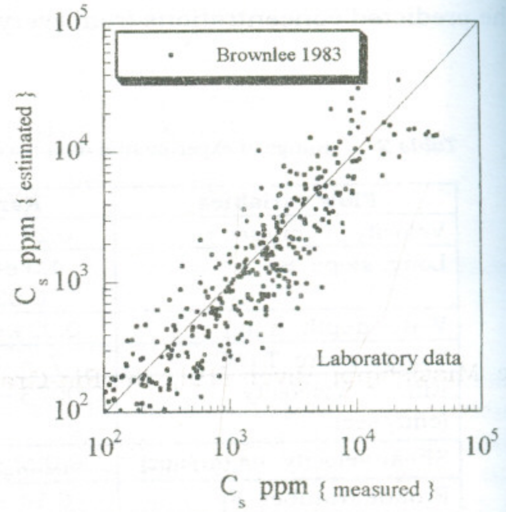

Figure 8 Verification of Brownlie's [2]equation laboratory using laboratory data

Table 4 The range of field data used for verification

Flow variables	Range	Sediment variables	Range
velocity V (m/sec)	0.25 ~ 2.32	Particle size d_m (mm)	0.16 ~ 1.9
Long. slope S	3.4 e-05 ~ 0.0029	Sediment Conc. C_S (ppm)	13 ~ 9970
Water depth h (m)	0.06 ~ 12.28		
Temperature T (°C)	0 ~ 29		
Kin. Viscosity ν(cm²/sec)	0.008 ~ 0.02		
Shear velocity u* (m/sec)	0.025 ~ 0.22		
Froude Number F_r	0.05 ~ 0.6		

Table 5 Accuracy of formulas for total sediment discharge, { 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
Engelund and Hansen [1]	140	3.60	7.35	14	26	44
Ackers and White (d_{50})[13]		1.82	4.03	14	33	55
Yang (d_{50}) [3]		1.24	1.56	27	50	67
Brownlie [2]		2.24	5.31	21	43	59
Shen and Hung [14]		2.06	3.82	24	35	50
Graf [15]		1.19	12.3	10	22	27
Inglis-Lacey [16]		1.80	9.79	9	23	39
Laursen [17]		1.08	4.60	6	17	39
Toffaleti [18]		1.27	5.25	7	17	37
The Presented Model		1.28	1.21	49	74	85

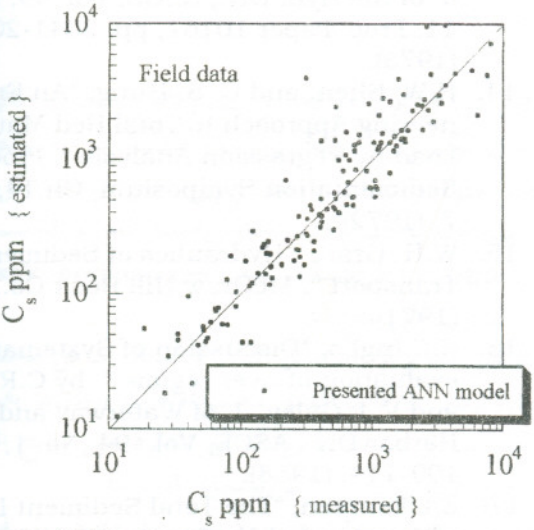

Figure 9 Verification of presented model using field data.

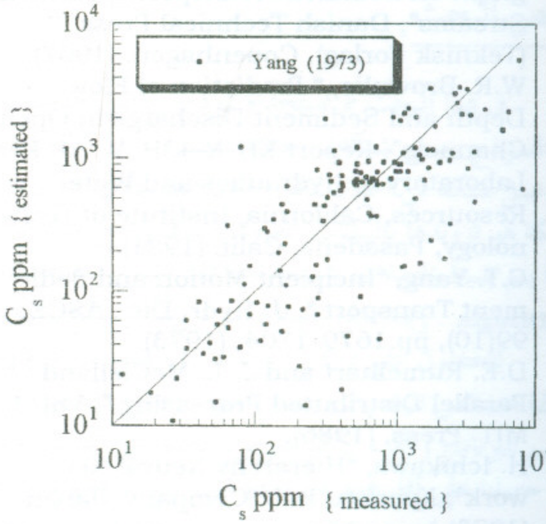

Figure 10 Verification of yang's [3] equation using field data.

CONCLUSIONS

A methodology developed in information technology and computer science can be applied within the hydraulics. The present study illustrates one particular aspect of hydroinformatics as an application on environmental problems. Knowing the data record for sediments in some station on a river, allows us to estimate the amount of contaminated transported sediment in another near location on such river or similar ones. The artificial neural network model can be successfully applied for sediment transport phenomena when the traditional approaches can not succeed with the uncertainty and the stochastic nature of the sediment movement. Providing the model with basic hydraulics data as input parameters using personal computer device, accurate estimate for sediment discharge will be obtained. Increasing input patterns for learning, which comes from well established data base system, will increase the accuracy of estimated values. Further research is needed to develop a unique universal model with complex threshold function and suitable dimensionless parameters to overcome the problems of scale effect of different rivers and streams. The author believes that percentage of sediment in suspension to the total sediment load is an effective parameter on results discrepancy ratio, however no field data are available yet to support such idea.

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REFERENCES

1. F. Engelund, and E. Hansen, "A Monograph on Sediment Transport in Alluvial Streams", Danish Technical Press (Teknisk Forlag), Copenhagen, (1967).
2. W.R. Brownlie, " Prediction of Flow Depth and Sediment Discharge in Open Channels", Report KH-R-43B, W. M. Keck Laboratory of Hydraulics and Water Resources, California, Institute of Technology, Pasadena, Calif, (1981).
3. C.T. Yang, "Incipient Motion and Sediment Transport ", J. Hydr. Div., ASCE, 99(10), pp.1679-1704, (1973).
4. D.E. Rumelhart and J. L. McClelland : " Parallel Distributed Processing ", Vol. 1, MIT Press, (1986).
5. H. Ichikawa, "Hierarchy Neural Network", Kyoristu Pub. Company, Japan, (1993).
6. H.P. Guy , B. Simons, and E. V. Richardson, " Summary of Alluvial Channel Data from Flume Experiments, 1956-1961, " USGS Professional Paper 462-I, pp.1-96, (1966).
7. G.P. Williams, "Flume Experiments on the Transport of a Coarse Sand", U.S. Geological Survey Professional Paper 562-B, pp.1-31, (1967).
8. G.P. Williams, "Flume Width and Water Depth Effects in Sediment Transport Experiments", U.S. Geological Survey Professional Paper 562-H, pp. 1-30, (1970).
9. B.D. Taylor, " Temperature Effects in Flows over Nonplaner Beds", J. Hyd. Eng., ASCE, Vol.100, No.Hy12, pp.1785-1807, (1974).
10. J.R. Barton, P.N. Lin, "Sediment Transport in Alluvial Channels ", Report No. 55JRB2, Civil Engrg. Dept., Colorado A&M College, Fort Collins, Colorado State, (1955).
11. N.H. Brooks, "Mechanics of Streams with Movable Beds of Fine Sand", Transactions, ASCE, Vol. 123, (1958).
12. H.A. Einstein, "The Bed-load Function for Sediment Transportation in Open Channel Flows", USDA, Soil Conservation Service, Tech. Bulletin, No. 1026, pp. 1-71, (1950).
13. P. Ackers, and W. R. White, "Sediment Transport : New Approach and Analysis", J. of the Hyd. Div., ASCE, Vol. 99, No. HY 11, Proc. Paper 10167, pp. 2041-2060, (1973).
14. H.W. Shen, and C. S. Hung, "An Engineering Approach to Total Bed Material Load by Regression Analysis ", Proc. of Sedimentation Symposium, Ch.14, pp.1-7, (1972).
15. W.H. Graf , " Hydraulics of Sediment Transport ", McGraw Hill Book Co., N.Y, (1971).
16. C.C.Inglis, "Discussion of Systematic evaluation of river regime ", by C.R.Neil, and V.J. Galey, J. of Waterway and Harbor Div., ASCE, Vol. 94, No. 1, pp. 109-114, (1958).
17. E.L.Laursen, "The Total Sediment Load of Streams ", J.Hy.Div, ASCE, Vol. 84, No. 1,pp. 1-36, (1958).
18. F.P. Toffaleti, "A Procedure for Computation of the Total River Sand Discharge and Detailed Distribution, Bed to Surface", Technical Report No.5,Committee on Channel Stabilization, US Army Corps of Eng.W.W. Experiment Station, Vicksburg, Miss, (1968).
19. P.R. Jordan, "Fluvial sediment of the Mississippi River at St. Louis, Missouri ", US Geological Water Supply Paper 1802, US Geological Survey, Washington, D.C, (1965).
20. C.F.Nordin : " Aspects of Flow Resistance and Sediment Transport, Rio Grande near Benadillo ",Water Supply Paper 1498-H, USGS, Washington, D. C, (1964).

21. D.W. Hubbell, D.Q. Matejka, "Investigations of Sediment Transportation, Middle Loup River at Dunning, Nebraska", Water Supply Paper 1476, USGS, Washington, D.C,(1959).
22. K. Shinohara, and T. Tsubaki : " On the Characteristics of Sand Waves Formed upon the Beds of Open Channels and Rivers", Reports of Res. Ins. Applied Mechanics, Kyushu University, Vol. 7, No. 25, pp. 1-13, (1959).
23. P. Ackers, Closure of Experiments on Small Streams in Alluvium", J. Hyd. Eng., ASCE, No. HY2, pp. 329-345, (1966).

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كميات الرواسب المتحركة فى القنوات المفتوحة : طريقة شبكات الخلايا العصبية

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ملخص البحث

فى هذا البحث تم استخدام نموذج رياضى حديث يستخدم لأول مرة فى مجال حركة ارواسب بالأنهار والمجارى المائية. هذا النموذج يسمى شبكات الخلايا العصبية، وهو شائع استعمالة فى مجال الكمبيوتر و الإلكترونيات والهندسة النووية. ويعتمد على عمل شبكة من الخلايا تماثل الخلايا العصبية فى جسم الإنسان ويصل بينها موصلات الأوامر. وأولى الخطوات بعد تكوين الشبكة هو تزويدها بالبيانات المعروفة مسبقا وناتج هذه البيانات المعروف أيضا. وتسمى هذه الخطوة بعملية التعليم للبرنامج . وفيها يتم ضبط المعملات باستخدام قاعدة تسمى قاعدة دلتا العامة (GDR) ، وطريقة تسمى " Back propagation Algorithm" . وبعد هذه العملية يتم تزويد البرنامج بالبيانات المراد الحصول على ناتج لها.

للحصول على تركيز الرواسب فى المياه، سواء كانت الزاحفة على القاع أو المعلقة فى المياه، تم استخدام كل المتغيرات المتعلقة بخصائص المياه والرواسب نفسها. وقد استخدمت النتائج المعملية لبعض الأبحاث المنشورة مسبقا؛ جزء منها بغرض التعليم للبرنامج والجزء الآخر بغرض التحقق من النتائج. ومن خلال الدراسة تم استبعاد المتغيرات غير المؤثرة على الناتج النهائى حتى حصلنا على أقل عدد من المتغيرات. كما تم معايرة معاملات النموذج الرياضى حتى تلائم المشكلة المدروسة.

تم التحقيق من نتائج النموذج باستخدام بيانات معملية وحقلية مأخوذة من أبحاث منشورة مسبقا. وتم مقارنة دقة النتائج مع نتائج بعض المعادلات المنشورة مسبقا والخاصة بحساب تركيز الرواسب. وقد أثبتت الدراسة أن النموذج يعطى نتائج دقيقة وجيدة ويمكن استخدامه بتوسع فى مجال حركة الرواسب .