CLASSIFICATION OF BED CONFIGURATIONS USING ARTIFICIAL NEURAL NETWORKS

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INTRODUCTION

In natural rivers and small streams, the bed forms are shaped by complex interaction between the flow and the sediments. Bed forms are classified into several types such as: ripples, dunes, antidunes, bars and washed flat bed according to their flow regime. The analysis of flow field structure, bed roughness, flow resistance, sediment discharge and stage-discharge relation are strongly related to the shape and type of such bed forms.

In this study, artificial neural networks approach is applied to make classification for the bed forms types. The back Propagation Algorithm is adopted for training the net with sufficient number of data sets contain flow as well as sediment properties. The results are verified and the model gives a good agreement with observed data.

PREVIOUS CONVENTIONAL METHODS FOR CLASSIFICATION

Most predictions of bed forms are based on empirical or semi-empirical analyses. Only plain graphical representation is given by the different investigators. In each method only two variables, different from model to another, are used to represent the effective flow and sediment parameters on the formation of different bed forms for all flow regimes. Even thought those methods were criticized that they are of questionable accuracy, they furnish a strong background about the most dominant variables in bed forms classification. In conclusion, one can recognize that two variables are not enough to represent the problem. These effective variables may be summarized as follows:

$$f\ (\Psi,\ F_n,\ R_{e*}\ ,\ w_0 / u_*,\ h / d_{50}\ ,\ h / B,\ I\ )\ =\ 0 \qquad (1)$$

where $\psi = hI / sd_{50}$ is the dimensionless tractive shear stress, s is the specific gravity = 1.65 for sand, d_{50} is the mean particle diameter, h is the water depth, I is the longitudinal slope, $F_n = u_m / \sqrt{gh}$ is the Froude number, u_m is the mean velocity, g is the gravitational acceleration, $R_{e*} = u_* d_{50} / \nu$ is the shear velocity Reynolds number, u_* is the shear velocity, ν is the kinematic viscosity, w_0 / u_* is the dimensionless suspended sediment parameter, h / d_{50} is depth scale ratio, and h / B is width scale ratio.

ARCHITECTURE OF NEURAL NETWORK

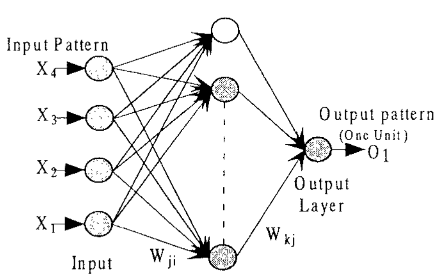

Fig.1 Multilayer feedforward Network.

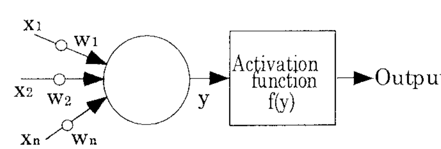

Fig. 2 The artificial neuron.

The ANN is composed of basic units called neurons. Each neuron receives input data, and processes it, then delivers a single output as a signal. The input can be raw data or the output of other neurons. The output may be final product, or an input to another neuron. The neurons are often grouped in a layer. The layers may be classified into three types: the input layer that receives data from outside and send it to the next layer without processing, the hidden layer that gives the network the ability to deal robustly with inherently nonlinear and complex problems, and finally the output layer that receives signals from previous layer, and delivers the output of the network, as shown in **Fig. 1**. In **Fig. 2**, the output of a neuron is calculated with an activation function that is applied to the weighted sum of inputs to the neuron. The selected function is called sigmoid function $f(y) = 1/\{1+\exp(-\alpha \sum wx)\}$, where x is the input to the neuron, w is the weight in the connection, and *f(y)* is the output. Weights are important because the network is repeatedly adjusted them until it produces the desired outputs. For training the network, the Back-Propagation Algorithm is utilized by propagating the error backward from output layer toward the input layer, and adjusting the weights on the connections.

EXPERIMENTAL DATA USED FOR TRAINING THE NETWORK

The most reliable published data sets for channels with movable bed that comprise a wide range of variables are those of Guy, et al. (2). The data are consisting of 10 different groups. The experiments 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) long, the smaller one was 2 ft (0.61 m) wide, 2.5 ft (0.76 m) deep and 60 ft (18.29m) long. Almost all the types of bed forms are resulted in the experiments: ripples, dunes, transition, and antidunes. The group of data contains of 333 data set. A number of 187 data sets are used for training the network, while the other 146 data sets are used for verification. The range of measured variables used in the training sets is summarized in **Table 1**.

Table.1 Range of training data

	Range
I	0.000055~0.01928
h/B	0.02375~0.445
h/d	124.54~1748.6
Ψ	0.026101~22.389
U_*/w_0	0.2112~7.6642
Re_*	2.0959~122.92
Fn	0.14~1.7

The network basic structure is consisted of the input layer with seven neurons representing the input parameters of Eq. 1, the hidden layer with a certain number of neurons (under investigation), and the output layer with 4 neurons representing the types of bed forms as digital numbers (ripples, dunes, transitions, and antidunes).

The network parameters are calibrated to give the most accurate results. The shaping ratio coefficient α is recommended to be equal 1.0, the number of neurons in the hidden layer is adjusted to be 7 neuron, the learning rate ε is taken equal to 0.075.

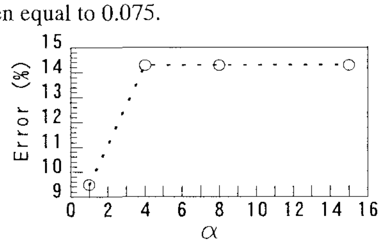

Fig.3 Effect of changing α on results

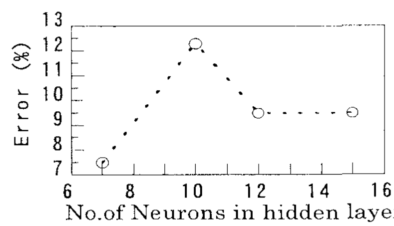

Fig.4 Effect of changing No. of neurons

VERIFICATION OF THE MODEL

Three previous methods are selected for the comparison with the presented model. Simons and Richardson (1966) see Ref. (1), made a graphical analysis relating between bed stream power, τU_m and the median fall diameter of bed sediment. Athaullah (1968), see Ref. (1), delineated different flow regimes based on Froude number F_n and the relative roughness without distinguishing between dunes and ripples. van Rijn (1984), see Ref. (1), classified bed forms dependh / d_{50} ing on two parameters; one of them is the particle diameter, and the other is the transport –stage parameter, T. The comparison is done on the same 146 predicted data sets. The percentage of error in classification for each method is shown in table 2. The number of miss-classified points in each zone is also tabulated. From the table it is clear that the presented approach gives better results than others do.

Table.2 Comparison with previous studies

Method	Data No.	R⇔D	R⇔F	R⇔T	D⇔T	D⇔F	T⇔A	F⇔A	Error %
The present model	146	2	0	1	5	1	1	1	7.5
Simons(1961)		5	2	0	14	2	3	4	20.5
Athaullah(1968)				0	8		0		6.0
Van Rijn(1984)		13		0	13		8		23.0

CONCLUSIONS

The neural networks model can be successfully applied for classification of bed configurations in the bottom of streams when conventional approaches can not succeed. Increasing the input patterns for learning the network with a wide range of variables consequently increases the accuracy of the model. Field data are strongly needed to verify the applicability of this approach on natural rivers.

REFERENCES

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