Filtering of the Bottom Shear Stress under Wave-Current Combined Flows by Using the Artificial Neural Networks

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Abstract

This paper presents the estimating of the bottom shear stress under wave-current interactions by using the Artificial Neural Network. The estimated value is expressed in terms of the relevant known information of the wave and current properties. Back propagation network was adopted and solved by the Levenberg-Marquardt algorithm. This is for speeding up the solutions of the network. The network architecture was made by trial and error so as to find the best network for this particular problem. This was finally found to be a 6-3-1 network. It is also found that the network can learn well for the data in the calibration stage. The efficiency index is nearly 100%. This indicates an alternative way to estimate the shear stress.

1 Introduction

In attempting to predict the sediment transport rate in a coastal regime, it is vital that one can accurately prescribe the hydrodynamics of the flow field. The process of sediment entrainment is dependent on the instantaneous near-bed fluid velocity and also bottom shear stress. Therefore, to accurately estimate the bottom shear stress is one of the challenging task for engineers and scientists.

Recently, there have been some well-known analytical models for the prediction of the bottom shear stress, e.g. GM(Grant and Madsen, 1979), TS(Tanaka and Shuto, 1981), CJ(Christoffersen and Jonsson, 1985), OY(O' Connor and Yoo, 1988), and MS(Myrhaug and Slaattelied, 1990). However, due to the non-linearity of wave and current flow fields and also the model characteristics, discrepancies between the measured and computed results may rise up to ± 50%. Soulby et al.(1993) also found that computational results among conventional models are 4 time differences. Therefore, it is rather difficult to select one best model. Then, he proposed a new method by making a parameter optimization to the model results.

Use of neural network techniques to solve problem in civil engineering began in the late 1980s(Flood and Kartain, 1994a). Their applications to simulation and forecasting problems in water resources are few and relatively recent, e.g. French et al.(1992) to forecast rainfall in space and time domain, Hsu (1995) and Crespo and Mora(1993) to forecast run-off from rainfall.

Instead of using a method similar to Soulby et al.(1993), the present paper is the first attempt to apply the Artificial Neural Network to estimate the mean bottom shear stress under wave-current interactions. Back Propagation network is adopted and solved by the Levenberg-Marquardt algorithm.

The experimental data are summarized from reliable experiments of Kemp and Simons (1982,1983), Simon et al.(1988), and Supharatid et al.(1992).

2 Method of study

2.1 Back propagation network

Background

BP network was developed by Rumelhart et al.(1986). The multiple-layer perceptron(see Fig. 1) was used in the learning process between input and output patterns. The BP network is based on a supervised learning technique that compares the computed output to the target output and then readjust the weights backward in the network. The same input is presented to the network for the next time, therefore the computed output will be closer to the target output.

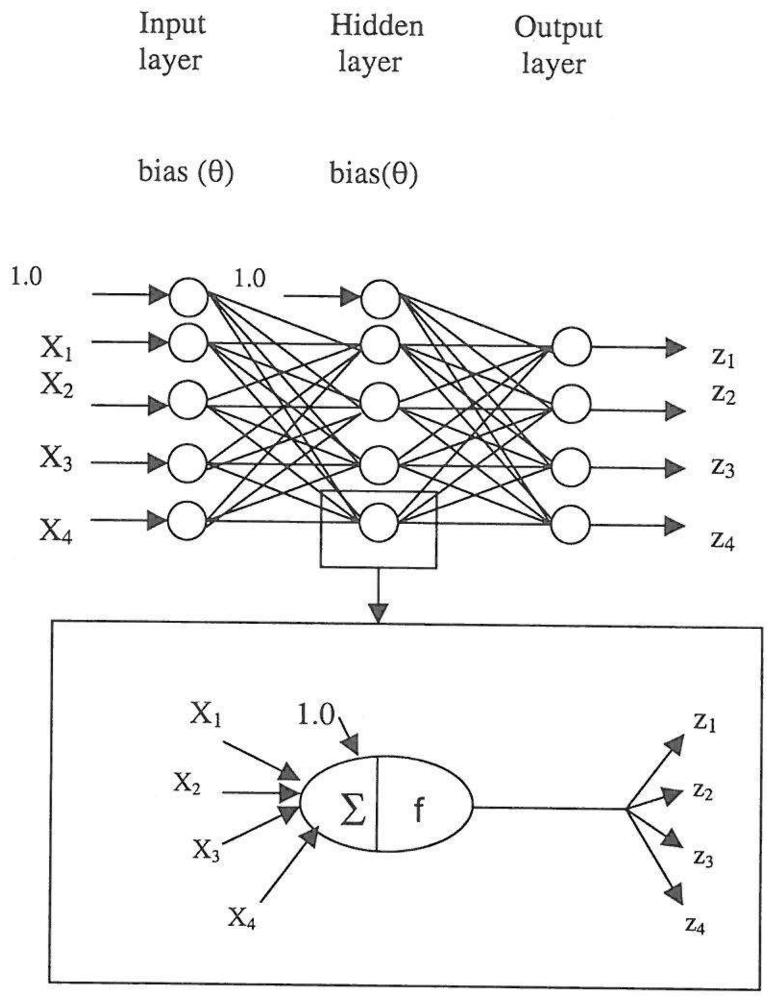


Fig. 1 BP network architecture

In Fig. 1, the input nodes receive the data denoted by X_i (i = 1 to 4) and pass them on to the hidden layer nodes. Each one of them collects the input from all input nodes after multiplying each input value by a weight (w_i), attaching a bias(θ) to this sum(Σ), and then passing on the result through a non-linear function(f). This result forms the input for the output later that operates identically to the hidden layer. The resulting transformed output from each node(z_i, i = 1 to 4) is the one obtained from the network.

Levenberg-Marquardt back propagation algorithm

The Levenberg-Marquardt algorithm(Scales, 1985) is a variation of Newton's method that was designed for minimizing functions that are sum of squares of the non-linear functions. By considering a feed-forward network, the Levenberg-Marquardt back propagation algorithm can be summarized as follows:

1) Initialize all weights(w_i) and biases(θ) to small random numbers
2) Present a training pair of input and output units
3) Compute the network output(z_i) starting with the input layer and proceeding layer by layer toward the output layer. The non-linear function used in the present study is the logistic sigmoidal function(Patterson, 1996)
4) Compute the errors and sum of squared errors(SSE) over all input patterns by Eqs. (1) and (2),respectively.

$$V_i = t_i - z_i \quad (1)$$

$$SSE = \sum_{i=1}^{N} V_i^2 \quad (2)$$

where V_i = Errors for each data pattern, t_i = target output

5) Compute the Jacobian matrix of the error, J(w)

$$J(w) = \begin{bmatrix} \frac{\partial V_1}{\partial w_1} & \frac{\partial V_1}{\partial w_2} & \cdots & \frac{\partial V_1}{\partial w_n} \\ \frac{\partial V_2}{\partial w_1} & \frac{\partial V_2}{\partial w_2} & \cdots & \frac{\partial V_2}{\partial w_n} \\ \vdots & & & \vdots \\ \frac{\partial V_N}{\partial w_1} & \frac{\partial V_N}{\partial w_2} & \cdots & \frac{\partial V_N}{\partial w_n} \end{bmatrix} \quad (3)$$

where N = Number of data patterns, n = number of all weights and biases in the network considered

6) Compute the adjusted weight, Δw_k

$$\Delta w_k = -\left[J^T(w_k)J(w_k) + \mu_k I\right]^{-1} J^T(w_k)V(w_k) \quad (4)$$

$$w_{k+1} = w_k + \Delta w_k \quad (5)$$

where μ_k= Some small numbers(Adaptive number), I = identity matrix

The advantage of this algorithm is that as μ_k is increased it approaches the steepest decent algorithm which is used in the standard Back propagation network. However, when μ_k is decreased to zero, it becomes the Gauss-Newton algorithm. Martin et al. (1999) suggested that μ_k should be started with small value(≈0.01) and during the computation, μ_k is adapted according to Eqs. (6) and (7). This algorithm provides a nice compromise between the speed of Newton's method and the gauranteed convergence of steepest descent.

$$\mu_{k+1} = \mu_k / 10 \text{ when } \Delta < 0 \quad (6)$$

$$\mu_{k+1} = 10\mu_k \text{ when } \Delta > 0 \quad (7)$$

where μ_{k+1}, μ_k = Values at the new and previous time steps, respectively. Δ = SSE (k+1)-SSE(k).

7) Repeat steps 3 to 6 for all data patterns, until the sum square errors have been reached an acceptable value.

2.2 Experimental data employed

The present paper has selected some reliable data from several sources. However, there still have few experiments of waves and currents using the wave tank. The relevant data of wave and current properties are summarized in Table1.

Table 1 Data employed in the present study

Authors	Test	T(sec)	H(m)	D(m)	Uc(m/s)	ks(m)	α(deg.)	$\tau_{s\,(N/m2)}$
Kemp & Simons (1982)	WCR1	1.006	0.0227	0.201	0.185	0.025	0	0.328
	WCR3	1.006	0.0316	0.201	0.185	0.025	0	0.372
	WCR4	1.006	0.0406	0.201	0.185	0.025	0	0.405
	WCR5	1.006	0.0466	0.201	0.185	0.025	0	0.35
Kemp & Simons (1983)	WDR1	1.003	0.0279	0.2	0.11	0.0247	180	0.111
	WDR2	1.003	0.0334	0.2	0.11	0.0247	180	0.15
	WDR3	1.003	0.0397	0.2	0.11	0.0247	180	0.173
	WDR4	1.003	0.0505	0.2	0.11	0.0247	180	0.177
	WDR5	1.003	0.0591	0.2	0.11	0.0247	180	0.204
Simons et al. (1988)	RDWCW1	0.7	0.14	0.3	0.075	0.0204	0	0.0436
	RDWCW2	0.7	0.184	0.3	0.075	0.0204	0	0.0458
	RDWCW3	0.7	0.211	0.3	0.075	0.018	0	0.0529
	RDWCW4	0.7	0.222	0.3	0.075	0.018	0	0.0518
	RDWCM1	0.7	0.118	0.3	0.195	0.0222	0	0.277
	RDWCM2	0.7	0.15	0.3	0.195	0.0216	0	0.316
	RDWCM3	0.7	0.172	0.3	0.195	0.0219	0	0.35
	RDWCM4	0.7	0.182	0.3	0.195	0.0216	0	0.354
	RDWCS1	0.7	0.099	0.3	0.25	0.0294	0	0.528
	RDWCS2	0.7	0.129	0.3	0.25	0.0294	0	0.54
	RDWCS3	0.7	0.151	0.3	0.25	0.0294	0	0.599
	RDWCS4	0.7	0.163	0.3	0.25	0.03	0	0.578
	RIWCW1	1	0.196	0.3	0.075	0.0204	0	0.0408
	RIWCW2	1	0.295	0.3	0.075	0.0201	0	0.0372
	RIWCW3	1	0.385	0.3	0.075	0.0156	0	0.0389
	RIWCW4	1	0.505	0.3	0.075	0.0156	0	0.0671
	RIWCM1	1	0.135	0.3	0.195	0.0219	0	0.294
	RIWCM2	1	0.227	0.3	0.195	0.0216	0	0.347
	RIWCM3	1	0.305	0.3	0.195	0.0216	0	0.372
	RIWCM4	1	0.407	0.3	0.195	0.0216	0	0.348
	RIWCS1	1	0.12	0.3	0.25	0.0294	0	0.54
	RIWCS2	1	0.201	0.3	0.25	0.0294	0	0.626
	RIWCS3	1	0.277	0.3	0.25	0.0297	0	0.542
	RIWCS4	1	0.369	0.3	0.25	0.03	0	0.543
Supharatid et al. (1992)	W4C1CR	1.3	0.1	0.3	0.0707	0.00693	0	0.178
	W4C2CR	1.3	0.094	0.3	0.1193	0.0163	0	0.339
	W4C1OR	1.3	0.0941	0.3	0.1186	0.0128	180	0.249
	W4C2OR	1.3	0.0975	0.3	0.1474	0.0184	180	0.293

T = wave period, H = wave height, D = flow depth, U_c = averaged current velocity
K_s = Nikuradse roughness, α = angle between wave and current, τs = Time-mean bottom shear stress

In the present study, the input units are the wave and current properties(see Table 1) which can be expressed by Eq. (8).

$$\tau_s = f(T, H, D, U_c, k_s, \alpha) \quad (8)$$

The data are divided into two parts, 2/3 for calibration and 1/3 for validation. The calibration stage is used for training the network, i.e. for determining all weights and biases. In the validation stage, the network after having been trained, is used to check if it still performs satisfactorily with the data that have not been used during the network training. It has to be mentioned that due to limitation of experimental conditions, input variations are quite narrow in magnitude. Therefore, applicability of ANN for the input data outside these ranges should be used with caution.

2.3 Performance statistics and data processing

The following performance statistics are used in order to evaluate the performance of the network.

Efficiency index(EI)

Nash and Sutcliffee(1970) proposed the efficiency index for measuring the model performance:

$$EI = (ST - SSE)/ST \quad (9)$$

$$ST = \sum_{i=1}^{N} (t_i - \bar{t})^2 \quad (10)$$

where ST = Total variation, SSE = sum squared errors(Eq. (2)), $\bar{t}$ = Mean value of the target($\sum_{i=1}^{N} t_i / N$), N = number of data points

Root mean squared error(RMSE)

$$RMSE = (SSE/N)^{1/2} \quad (11)$$

Mean absolute deviation(MAD)

$$MAD = \frac{1}{N}\sum_{i=1}^{N} | t_i - O_i | \quad (12)$$

In the calibration and validation stages, before presented to the network, the data are transformed by linear transformation to interval [0.1, 0.9]. This is due to the reason that the logistic sigmoidal function has an output value lies in interval[0, 1]. Equations (13) and (14) are used to transform the data before presenting to the network and to transform back into the original values, respectively.

$$X' = \frac{0.8(X - a)}{(b - a)} + 0.1 \quad (13)$$

$$X = \frac{(b - a)(X' - 0.1)}{0.8} + a \quad (14)$$

where X, X′ = Original and transformed data, a, b = Minimum and maximum values of the data.

As pointed out by many researchers, one of the weak points of the BP networks is slow convergence. Therefore, to speedup the solution, the Levenberg-Marquardt algorithm which is a variation of Newton's method was applied in the present study. The stopping rule was based on the relative error of the SSE(Eq. (15)).

$$\left| \frac{SSE(new) - SSE(old)}{SSE(old)} \right| \le 10^{-5} \quad (15)$$

For the present study, a simple network architecture with one output layer was selected. Correspondingly, the network structure for this particular case study was made by trials and errors. Finally, the best network was found to be 6-3-1 as shown in Fig. 2.

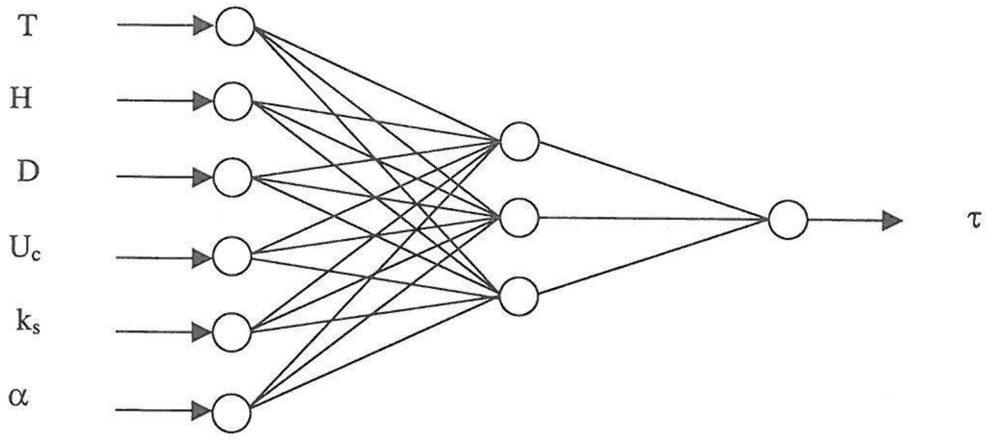


Fig. 2 A 6-3-1 network using in the present study

3 Result discussions

3.1 Best network selection

In the present study, the input and output units are fixed at 6 and 1, respectively(see Eq. (8)). The units in the hidden layer are varied from 2 to 5. Table 2 shows the calculated statistical parameters of 4 networks in the present study. It is found that a 6-3-1 network is the best for this particular study. It is clearly seen that the effective index is high as 0.99, indicating an acceptable model. However, it is about 0.8 for the data in the validation stage. The RMSE and MAD for the data in both stages show also reasonable results.

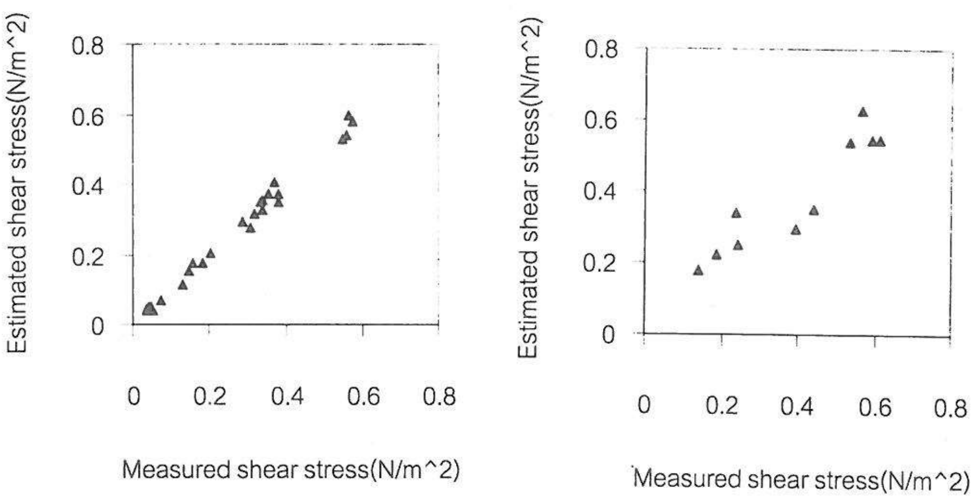
Table 2 Statistical parameters

Network	EI(C)	EI(V)	RMSE(C)	RMSE(V)	MAD(C)	MAD(V)	Best net.
6-2-1	0.95		0.186		0.137		
6-3-1	0.99	0.78	0.016	0.066	0.013	0.055	*
6-4-1	0.96		0.139		0.115		
6-5-1	0.96		0.166		0.129		

(C) : Calibration stage, (V) : Validation stage

3.2 Dispersion diagram for network 6-3-1

Comparisons between the calculated and measured mean bottom shear stress for the calibration and validation stages are shown in Figs. 3(a) and 3(b), respectively. Excellent agreements are found for the calibration stage, indicating excellent performance of the network used in the present study. However, for the validation stage, the network gives some small deviations compared to the measured values.



(a) Calibration stage (b) Validation stage

Fig. 3 Comparisons between the network outputs and the measured values

4 Conclusions

This paper presents the estimating of the mean bottom shear stress under wave-current interactions by using the Back Propagation Network. The estimated value is expressed in terms of the relevant known information of the wave and current properties i.e. wave period, wave height, water depth, interacting angle, averaged current velocity, and the bottom roughness. The Levenberg-Marquardt algorithm was adopted to speed up the solutions. The network architecture is made by trial and error so as to find the best network for this particular problem. This was later found to be 6-3-1 network. It was also found that the network can learn and estimate well the data in the calibration stage. However, small deviations were found in the validation stage of data. It has to be realized that due to a narrow band of the input variables used in the present study, application of ANN to field conditions should be used with caution. It is recommended that if there are field data, the network should be trained so as to find the best weights and biases for that particular problems.

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