

STABILITY ANALYSIS OF RUBBLE MOUND BREAKWATER USING ANN

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ABSTRACT

The stability analysis of coastal structure is very important because it involves many design parameters to be considered for the safe and economical design of structure. In the present study neural network technique is adopted to predict the stability number and damage levels of rubble mound breakwater. Four network models were constructed based on the input parameters, which affect the stability of breakwater. A good correlation is obtained between network predicted stability number and estimated ones.

Key words: stability, neural network, rubble mound breakwater, stability number and damage levels

INTRODUCTION

Breakwaters are widely used all over the world mainly to provide a safe shelter, devoid of wave action. This protection is primarily designed to attain tranquility condition in ports and harbors to enable safe loading and unloading operations for vessels. The most commonly used breakwaters are of rubble mound type which consists of one or two layers of heavier armor stones, one or two filter layers consisting of relatively smaller stones and a core of quarry run. The design of the breakwater section, which is normally of a trapezoidal shape, is described in great detail by US Army Corps of Engineers (SPM, 1984). The theoretical equations are used to calculate the armor weight and stability of breakwater. These formulae are derived after conducting many experiments on breakwater by varying slope, armor weight, permeability and different thickness of armor layer. But these formulae show some disagreement between each other, therefore a number of studies have been carried out to develop new empirical formulae, which also shows less improvement (Mase et al, 1995) Stability analysis of breakwater can be further improved using artificial neural network.

A neural network is an information processing system modeled on the structure similar to that of human brain (Nakano et al, 1989; Ichikawa 1993, Nielsen 1988). Networks have an ability to recognize the hidden pattern in the data and accordingly estimate the values. The biggest merit is its ability to deal with fuzzy information whose interrelation is ambiguous or whose functional relation is not clear. In more practical terms networks are non-linear modeling tools and they can be used to model complex relationship between input and output system. Earlier applications of neural networks for stability analysis of rubble mound breakwater by Mase et al 1995 and Kim and Park 2005.

The four neural network models are constructed based on the major input parameters that affect the stability of structure. Input parameters considered in present study are permeability of breakwater (P), storm duration (N), significant wave height (H_s), mean wave period (T_m), damage level (S_d), relative armor weight (Δ), nominal diameter of stone (D_{n50}), spectral Shape (SS), slope angle ($\cot\alpha$), wave steepness (H_s/L_s), relative water depth (d/L_s) and relative wave height (d/H_s).

STABILITY NUMBER ESTIMATION USING EMPIRICAL METHODS

Hudson formula

Hudson (1959) proposed a new formula to calculate the weight of primary armor units. The stability formula was developed by equating the total drag and inertial force of wave to relevant component of the individual units. As per Hudson, the weight of the individual armor unit is as follows.

$$w = \frac{w_r H^3}{K_D (S_r - 1)^3 \cot \alpha} \quad (1)$$

Where w_r : Unit weight of armor unit in N/m^3 , H: Design wave height, S_r : Specific gravity of armor units, K_D : Stability coefficient and α : Slope of breakwater measured from the horizontal level in degrees.

The stability number N_s is expressed as

$$N_s = \frac{H}{\Delta D_{n50}} = (K_D \cot \alpha)^{1/3} \quad (2)$$

Van der Meer formula

Van der Meer (1988) proposed stability equations for rubble mound breakwater based on extensive laboratory studies at Delft Hydraulics Netherlands. His results indicate that the type of wave breaking near the breakwater structure. He observed that minimum stability for transition from surging to plunging waves called collapse waves. He derived two set of formula for computation of stability number as follows.

For plunging waves, when $\xi_m < \xi_{mc}$

$$N_s = \frac{H_s}{\Delta D_{n50}} = 6.2 P^{0.18} \left(\frac{S_d}{\sqrt{N_w}} \right)^{0.2} \xi_m^{-0.5} \quad (3)$$

For surging waves, when $\xi_m > \xi_{mc}$

$$N_s = \frac{H_s}{\Delta D_{n50}} = 1.0 P^{-0.13} \left(\frac{S_d}{\sqrt{N_w}} \right)^{0.2} \sqrt{\cot \alpha} \xi_m^P \quad (4)$$

Where H_s : Significant wave height, S_d : Damage level, Δ : Relative mass density of stone ($=S_r - 1$), P: Permeability of breakwater structure, N_w : Number of waves or (Storm Duration), D_{n50} : Nominal diameter of stone.

PROBLEM SET UP

Here an attempt is made to improve the stability formulae by considering other parameters like wave steepness, relative water depth, relative wave height, which are not considered in either of Hudson or Van der Meer stability formulae. Initially for the given experimental data set, stability number is calculated using empirical formulae as mentioned above and stability number given by Hudson is considered as measured and van der Meer formula as predicted. The graph is plotted using N_s measured v/s N_s predicted as shown in Fig 1.

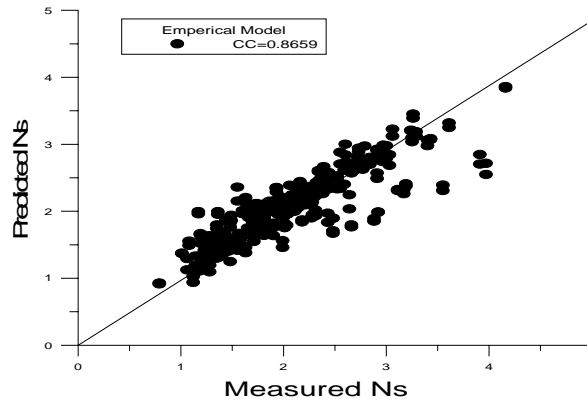


Fig. 1 Stability number (N_s) predicted (van der Meer) Vs measured (Hudson).

The coefficient of correlation between measured and predicted stability number is found to be 0.8659 and the degree of agreement between measured and predicted one is not so good. The scattering of predicted stability numbers from the measured ones can not be negligible. An alternative method called neural network is adapted to improve the correlation between the predicted and measured stability values.

In the present study, the network stability analysis is carried, using back propagation method. The input parameter considered for analysis are Permeability of breakwater, Number of waves, Significant wave height, Mean wave period, Damage level, Relative armor weight, Nominal diameter of stone, Spectral Shape, Slope angel, Wave steepness and Relative wave height. Based on these parameters the four network models are constructed with different parameters to predict the new stability number (N_s) are tabulated in Table-1.

Table-1 Input parameters used for ANN models

Model	Input Parameters
ANN1	$P, N_w, S_d, H_s, T_m, \Delta, SS, (d/H_s)$
ANN2	$P, N_w, S_d, T_m, \text{Cot}\alpha, D_{n50}, SS, (H_s/L_s)$
ANN3	$P, N_w, S_d, H_s, T_m, \text{Cot}\alpha, \Delta, SS, (d/L_s)$
ANN4	$P, N_w, S_d, H_s, T_m, \text{Cot}\alpha, \Delta, D_{n50}, SS, (d/H_s), (d/L_s)$

In first model ANN1 significant wave height H_s and mean wave period T_m are used instead of single parameter like surf similarity parameters used by Kim and Park (2005), also to consider the effect of depth of water in front of structure the relative wave height is used as another parameter. In second model ANN2 wave stiffness and Slope angle of breakwater are

considered to add the effect of varying slope of breakwater on stability. In third model ANN3 relative water depth used to consider the effect of water in front of structure. In last model ANN4 all parameters are considered which are mentioned in above three models.

WORKING PRINCIPLE OF NEURAL NETWORK

The feed forward neural networks have ability to approximate any continuous function or complex phenomena into a simple one. The working of neural network as described below. A feed forward neural network as shown in Fig 2, which consists of three layers namely input layer, hidden layer and output layer. The inputs to the network fed at input layer. The number of input nodes is equal to the number of input parameters used for analysis. The input nodes receive the data and pass them on to the next layer called hidden layer nodes. These nodes individually sum up the received values after multiplying each input value by a weight, and then they attach a bias to this sum. This is mathematically expressed as,

$$Z_k(x) = \sum_{j=1}^N w_{jk} \times T_r(s) + b_{ko} \quad (5)$$

$$s = \sum_{i=1}^M w_{ij} \times x_i + b_{jo} \quad (6)$$

Where x is input parameter, w_{ij} and w_{jk} are weight values, b_{jo} and b_{ko} are bias values, M is the number of nodes at input layer, N is the number of nodes at the hidden layer and $T_r(s)$ is the activation function. This activation is a non-linear sigmoid function expressed as

$$T_r(s) = \frac{2}{(1 + e^{-2s})} - 1 \quad (7)$$

s corresponds to the summation of inputs parameters with weights and bias values between input and hidden layer. Z_k is the output of hidden layers forms the input to the output layer. And pass through a linear transfer function called *purelin*, the output of purelin is network predicted output. In the present study the back propagation feed forward type network is used and the objective is to minimize the global error given as

$$E = \frac{1}{P} \sum E_p \quad (8)$$

$$E_p = \frac{1}{2} \sum (Z_k - T_k)^2 \quad (9)$$

P is the total number of training pattern, E_p is error for the p^{th} pattern, Z_k is network output at the k^{th} output node and T_k is the target output at the k^{th} output node.

NETWORK STABILITY ANALYSIS

The neural network learning is carried out with help of examples, training the network is kind of learning method. Since the neural network is an input and output system, the input data sets are essential to train the network models. The data sets can be obtained from the field observations or from the laboratory experiments. The data sets used in the present study are

experimentally generated by W.J Van der Meer at Delft Hydraulics, Netherlands on Rubble mound breakwater. The total 532 data sets are used among these 370 data sets are randomly selected for network training and 162 data sets are used for testing.

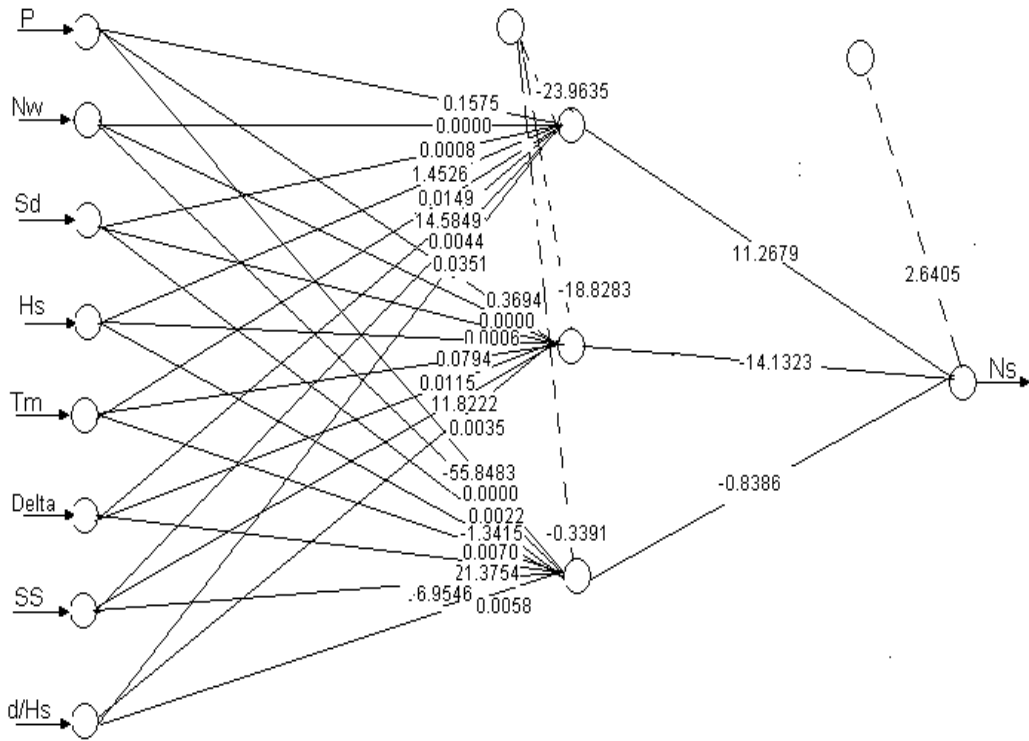


Fig. 3 Trained ANN1 model N 8-4-1, weights and bias values

The weights and bias values are as shown in Fig.2 represents the source of knowledge are obtained after the training process and these can be further used to predict the new stability number for unknown input parameters. Once the network is trained the weight and bias values got fixed and the representation of weights and bias values for ANN1 is as shown in Fig.2. The each input value gets multiplied with the weight and adds with the bias value. The total sum is the input to the hidden node pass through a transfer function as defined in equation 14. Expressing N_i as values of hidden nodes and F_i as transfer function of hidden node i , the stability number is estimated using following formulations:

The transfer function used at hidden layer is *tan sig* expressed as

$$\text{Transfer function } F_i = \left[\frac{2}{1 + \exp(-2 \times N_i)} - 1 \right] \quad \dots i=1 \text{ to } 3 \quad (10)$$

$$N_1 = P \times (0.1575) + Nw \times (0.0000) + Sd \times (0.0008) + Hs \times (1.4526) + Tm \times (0.0149) + \Delta \times (14.5849) + SS \times (0.0044) + (d/Hs) \times 0.0351 - 23.9535. \quad (11)$$

$$N_2 = P \times (0.3694) + Nw \times (0.0000) + Sd \times (0.0006) + Hs \times (-0.0794) + Tm \times (0.0115) + \Delta \times (11.5222) + SS \times (0.0035) + (d/Hs) \times (0.0281) - 18.8283. \quad (12)$$

$$N_3 = P \times (-55.8483) + Nw \times (0.0000) + Sd \times (0.0022) + Hs \times (-1.3415) + Tm \times (0.0070) + \Delta \times (21.3454) + SS \times (-6.9546) + (d/Hs) \times (0.0058) - 0.3391. \quad (13)$$

$$F_1 = (2 / (1 + \exp(-2 \times N_1))) - 1. \quad (14)$$

$$(15)$$

$$\begin{aligned}
 F_2 &= (2 / (1 + \exp(-2xN_2))) - 1. \\
 F_3 &= (2 / (1 + \exp(-2xN_3))) - 1.
 \end{aligned}
 \tag{16}$$

Where, N_1 to N_3 and F_1 to F_3 represent summation function and transfer function at each hidden node respectively.

$$N_S = F_1x (11.2679) + F_2x (-14.1323) + F_3x (-0.8386) + 2.6405.
 \tag{17}$$

RESULTS AND DISCUSSIONS

To find the better algorithm among three updated algorithms like LMA, SCG and GDA, four network models are trained and test for same number of hidden nodes and same number of epochs i.e. 4 hidden nodes and 200 epochs. The results obtained of same were tabulated as shown in Table-2 to Table-4.

Table 2 CC and MSE obtained using SCG algorithm with same number of epochs

Model	Network (Input parameter, epochs, nodes)	Train CC	Test CC	Mean square error
ANN1	8-4-200	0.8448	0.8431	0.116109
ANN2	8-4-200	0.8546	0.8051	0.160294
ANN3	8-4-200	0.8419	0.8310	0.123802
ANN4	8-4-200	0.8664	0.8453	0.075519

Table 3 CC and MSE obtained using GDA algorithm with same number of epochs

Mode	Network (Input parameter, epochs, nodes)	Train CC	Test CC	Mean square error
ANN1	8-4-200	0.8423	0.8236	0.121932
ANN2	8-4-200	0.7310	0.7195	0.280556
ANN3	8-4-200	0.8280	0.8089	0.129237
ANN4	8-4-200	0.8507	0.8407	0.080089

Table- 4 CC and MSE obtained using LM algorithm with same number of epochs

Model	Network (Input parameter, epochs, nodes)	Train CC	Test CC	Mean square error
ANN1	8-4-200	0.9974	0.9967	0.002088
ANN2	8-4-200	0.9668	0.9513	0.025134
ANN3	8-4-200	0.9992	0.9990	0.000618
ANN4	8-4-200	0.9999	0.9997	0.000110

From Table 2, 3 and 4, it can be found that Correlation Coefficients (CCs) and Mean Square Error (MSE) obtained for both training and testing for LMA is lesser compared to other two

algorithms are SCG and GDA. It is found that network predicted values exactly match with the measured stability number. High correlation is obtained for all the network models using LMA. Form this is observed that LMA is better algorithm for training the network models compared to SCG and GDA Later the details detailed analysis is carried out using LMA. It was also observed that from Table-4 the CC obtained for both training and testing is more than 0.99 except second model ANN2 and this model is devoid of relative armor unit parameter, shows is most important parameter.

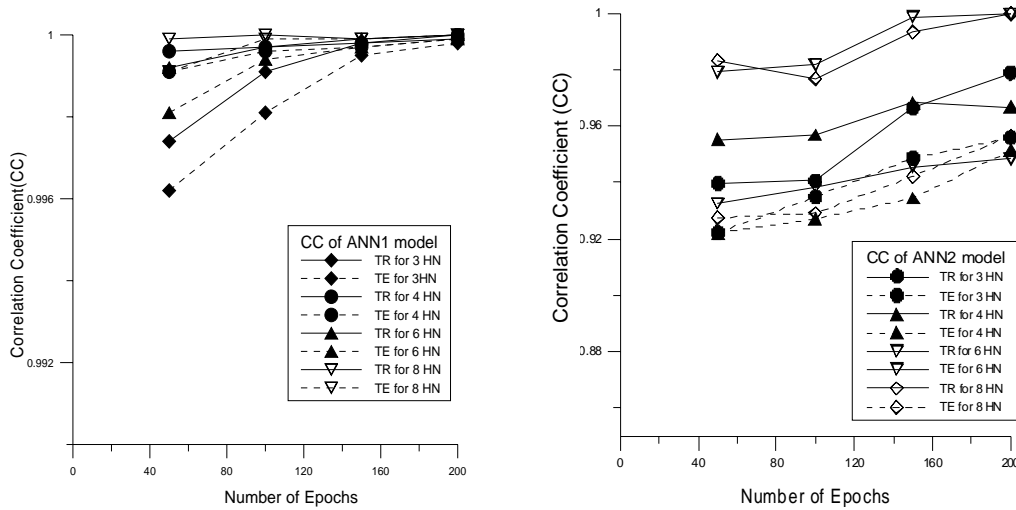


Fig. 3 Correlation Coefficient Vs Number of epochs of ANN1 and ANN2 model.

Further a detailed network analysis, were carried out using LMA from 3-8 hidden nodes for 50-200 epochs. The results of each model output is as shown in Fig. 3 it can be observed that there is improved in values of CCs, as the number of epochs and number of hidden nodes increases. Here TR represents training, TE-testing and HN-hidden nodes.

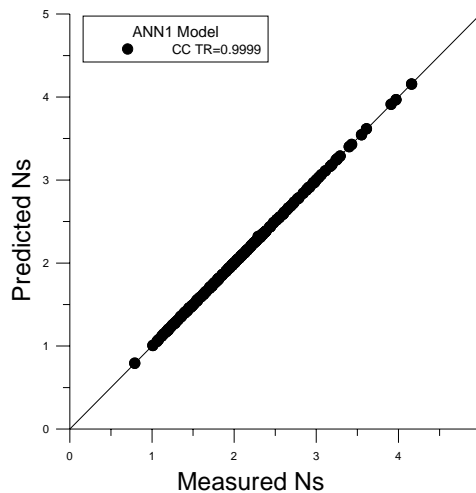


Fig. 4 Trained Correlation Coefficient between Measured and predicted stability numbers of ANN1- (N-8-6-1)

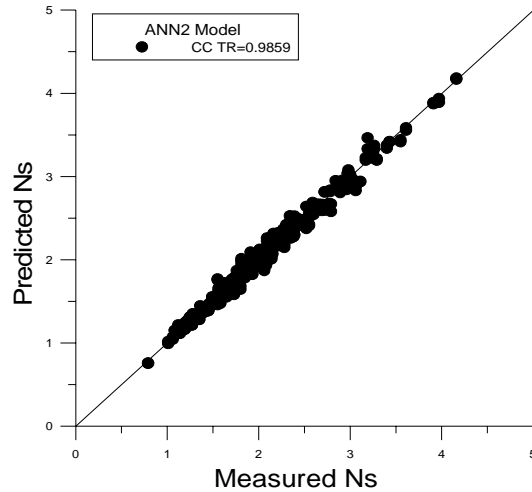


Fig. 5 Trained Correlation Coefficient between Measured and predicted stability numbers of ANN2- (N-8-6-1)

Network models are trained using LMA, the results of training and testing for two models ANN1 and ANN2 were plotted for network predicted stability numbers Vs measured stability numbers is as shown in Fig. 4 and to Fig. 5. A high Correlation Coefficient is obtained for first model ANN1 model that is 0.9999 and for second model ANN2 CC obtained as 0.9899. Later network models are used to predict the armor weights for two cases are considered separately. The design parameters used are as shown below.

Case 1: $d=4.5\text{m}$, $H_S=2\text{m}$, $T_S=10\text{sec}$, $\cot\alpha=3.0$, $P=0.2$, $N=3000$, $\Delta=1.74$, $\gamma= 2.74 \text{ ton/m}^3$ and

Case 2: $d=6.5\text{m}$, $H_S=3\text{m}$, $T_S=12\text{sec}$, $\cot\alpha=3.0$, $P=0.2$, $N=3000$, $\Delta=1.74$, $\gamma= 2.74 \text{ ton/m}^3$.

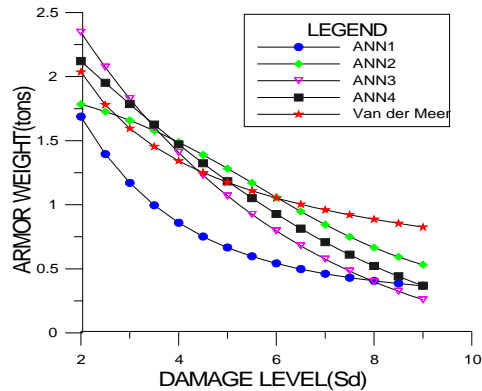


Fig. 6 Armor weight estimation using ANN Models and empirical formula- (Case-1)

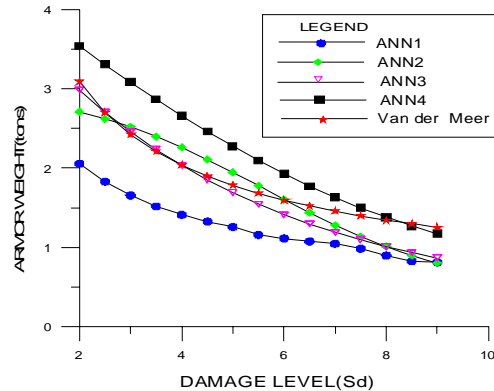


Fig. 7 Armor weight estimation using ANN Models and empirical formula- (Case-1)

Graph is plotted with armor weights Vs Damage level as shown in Fig. 6 and 7. It is found that in both the cases armor weights predicted by neural network models are much lesser than the van der Meer model (empirical formulae). It shows that one should analysis and design of breakwater based on empirical formulae and ANN techniques.

CONCLUSIONS

Based on the present study the following conclusions were drawn:

The stability of rubble mound breakwater predicted by the neural network is comparatively better than the empirical formula and the coefficient of correlation is much higher value than the van der Meer formula. The upgraded algorithm like LMA showed better improvement compared to other two algorithms like SCG and GDA. A high correlation coefficient is achieved for 8 hidden nodes at 200 epochs. The network predicts a relatively lesser armor weights compared to empirical model. From the network analysis found the relative armor weight is important parameter to be considered for the design of breakwater.

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