



Artificial neural network based breakwater damage estimation considering tidal level variation



Dong Hyawn Kim^{a,*}, Young Jin Kim^a, Dong Soo Hur^b

^a Department of Ocean Science & Engineering, Kunsan National University, Republic of Korea

^b Department of Ocean Civil Engineering, Gyeongsang National University, Republic of Korea

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ABSTRACT

A new approach to damage estimation of breakwater armor blocks was developed by incorporating a wave height prediction artificial neural network (ANN) into a Monte Carlo simulation (MCS). The ANN was used to predict the wave height in front of a breakwater, with both the deep water wave heights and tidal level being input to the ANN. The waves predicted by the ANN were comparable to those from a wave transform analysis. Using an ANN in wave prediction makes it possible to very simply and quickly obtain numerous waves near the breakwater. Eventually, the analysis time for the expected damage can be reduced. In addition, the effect of the tidal level on the expected damage was revealed by numerical examples. In these numerical examples, it was found that the tidal variation should be taken into account when estimating the expected breakwater damage.

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1. Introduction

Empirical models for breakwater damage prediction have been proposed by Hanzawa et al. (1996) and Melby and Kobayashi (1998), respectively. They modified stability number prediction models to obtain damage due to wave attack. Yagci et al. (2005) proposed ANN model to predict damage ratio of breakwater. Other soft computing based stability number prediction models such as by Mase et al. (1995), Kim and Park (2005) and Koc and Balas (2012) can also be modified for damage estimation.

It has been known to be a good measure of the lifetime breakwater damage under ocean wave attack. During the estimation process, uncertainties in the wave height and physical properties of the blocks can be incorporated. The yearly damages caused by storm waves accumulate until the end of its lifetime. Therefore, this method can also be used to determine the optimal armor block weight through a life cycle cost (LCC) analysis under the presence of design variable uncertainties.

In calculating the yearly damage to armor blocks, the significant wave heights in front of a breakwater are required. The significant wave heights can be estimated using a wave transform analysis. There are several numerical models that are generally used in the prediction of shallow sea waves, such as SWAN (Booij et al., 2006). These models are known to be very powerful and

have high accuracy. However, too much time may be spent in calculating a single wave height. To predict the expected breakwater damage, numerous wave transform analyses are required. Therefore, it is neither practical nor possible to use this method for design purposes. For this reason, the expected damage is usually found by using a probabilistic distribution of shallow sea waves, rather than deep sea waves. The probabilistic distribution in front of a breakwater is approximately estimated using several wave heights from a wave transform model. By doing so, the total analysis time for the expected damage can be reduced because only several shallow waves are required. This indirect approach, however, cannot consider the tidal variation in a coastal area because the newly established probabilistic distribution of shallow waves is based on a certain tidal level. Suh et al. (2003) developed an integrated analysis tool in which tidal variation can be considered during the expected damage estimation. However, this tool uses a certain type of numerical model with limited performance in predicting wave height, and it still requires a considerable amount of calculation time.

In this research, a new approach to expected damage estimation using an artificial neural network (ANN) was proposed. An ANN was applied in this study for two reasons. First, an ANN can predict shallow water waves very quickly after it is trained. This makes it possible to apply a type of random simulation method such as Monte Carlo simulation (MCS) to the expected damage estimation while still using a deep sea wave distribution. In addition, there is no limitation on the numerical models used. Any type of numerical model can be incorporated when preparing the training data for an ANN. Second, by using an ANN, the tidal

* Correspondence to: Department of Ocean Science & Engineering, Kunsan National University, San 68, Miryong, Gunsan, Jeonbuk 573-701, Republic of Korea. Tel.: +82 63 469 1862; fax: +82 63 463 9493.

E-mail address: welcomed@naver.com (D.H. Kim).

variation in front of the breakwater can also be considered. Therefore, more reasonable results can be obtained because the tidal variation is included as a random variable.

2. Artificial Neural Network

An ANN is very useful in many fields of engineering. It has been applied to diverse coastal engineering studies, including tidal level prediction (Lee and Jeng (2002)), wave height estimation (Deo et al., 2001; Agrawal and Deo, 2002), and wave run-up calculation (Medina, 2000). In addition, it has been used to predict the hydraulic stability and failure probability of rubble mound breakwaters (Kim and Park, 2005).

By imitating the learning capability of a living creature, an ANN can predict the desired outputs after it is trained with well-organized input-output pairs. An ANN comprises an input layer that receives input data, an output layer that provides prediction results, and more than one hidden layer interconnecting the first two layers, as shown in Fig. 1. Each layer has several nodes through which data are transferred from one layer to another. When there are L , M , and N nodes at each layer, and input $I_i (i = 1, 2, \dots, L)$ is given to the ANN, the j -th output at the hidden layer can be represented as Eq. (1)

$$H_j = f(\text{net}_j) \tag{1}$$

where $f(\cdot)$ refers to the activation function and net_j is the net input to the j -th node of the hidden layer, which is represented by

$$\text{net}_j = \sum_{i=1}^L W_{ji} I_i + b_j \tag{2}$$

In Eq. (2), W_{ji} denotes the weight between the input and the hidden layer and b_j is the bias at the hidden layer. Using those outcomes from the hidden layer, the j -th output layer node produces

$$O_k = f(\text{net}_k) \tag{3}$$

The net input to the k -th node is expressed by

$$\text{net}_k = \sum_{j=1}^M W_{kj} H_j + b_k \tag{4}$$

where W_{kj} is the weight between the hidden and the output layers and b_k is the bias at the output layer. Initially, these weight and bias values cannot be known. They need to be determined using an optimization process called training. For optimizing the weights, the objective function defined by Eq. (5) is used.

$$E = \sum_{\tau=1}^P \sum_{k=1}^N (D_k^{\tau} - O_k^{\tau})^2 \tag{5}$$

where P is the number of patterns in the training data and D_k^{τ} is the desired output that the ANN is required to predict. The optimal weights and biases can be found by minimizing the objective function.

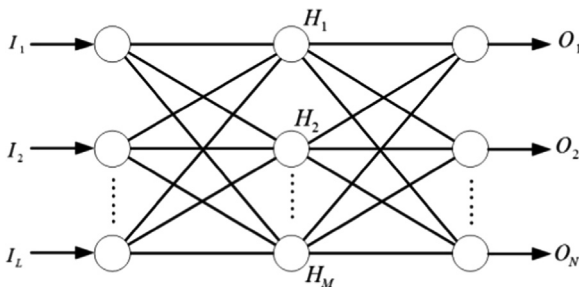


Fig. 1. Typical layout of neural network.

3. Expected Damage using ANN

3.1. Wave height at deep sea

Based on measurements, the significant deep sea wave heights are generally defined in the form of an extreme distribution (KORDI, 2005). The most widely used type of extreme value distribution is the well-known Weibull distribution, which can be written as

$$F(H_o) = 1 - \exp \left[- \left(\frac{H_o - C}{B} \right)^k \right] \tag{6}$$

where B , C , and k are the scale, location, and shape parameters, respectively.

3.2. ANN for wave height prediction

The significant wave height in front of a breakwater is affected by various factors such as the height and period of a deep sea wave, the water depth at the breakwater, water level, and boundary conditions. To obtain a wave height from a wave transform analysis, it is necessary to have detailed numerical models on hand together with the above conditions. However, most of these remain constant during wave transform. Only a few data points such as the water level and deep sea wave height are variables. In using an ANN for engineering applications, it is very important and practical to use the smallest possible number of inputs. Any redundant training data only increases the training time or even prevents it from being convergent.

There might still be uncertainty in the significant wave height predicted by an ANN. This type of uncertainty may be due to the fact that the training data are collected from a numerical model that is considered to be imperfect. Therefore, the following operation is applied to the predicted wave heights.

$$H_{1/3} = (1 + \alpha_{H_{1/3}}) H_{1/3e} \tag{7}$$

$$\sigma_{H_{1/3}} = \gamma_{H_{1/3}} H_{1/3e} \tag{8}$$

where $H_{1/3e}$ is the significant wave height predicted by an ANN and $\alpha_{H_{1/3}}$ and $\gamma_{H_{1/3}}$ denote the bias and coefficient of variation, respectively (Takahashi et al., 1998).

3.3. Expected damage level

Fig. 2 shows a flowchart for the expected damage estimation using an ANN. A significant wave height at the deep sea is generated from a Weibull distribution. Then, it is fed into the ANN together with the water level in front of a breakwater. This water level is also generated from a normal distribution. The trained ANN predicts a significant wave height in front of a breakwater. To account for the uncertainty within the predicted wave height, Eqs. (7) and (8) are applied to the predicted wave height. A predicted wave height greater than a predetermined critical one may cause a breakwater to be damaged. Therefore, damages from severe wave heights are accumulated during its lifetime. Repeating this process, the damage level converges to a certain value, which is the so-called expected breakwater damage.

The damage level is calculated by reformulating van der Meer's stability formula (van der Meer 1988) as follows:

$$N_0 = \left[\frac{1}{3.75} \left\{ \frac{H_{1/3}}{(S_{\gamma} - 1) D_n} \left(\frac{H_{1/3}}{L_0} \right)^{0.2} - 0.85 \right\} \right]^2 N^{0.5} \tag{9}$$

where S_{γ} and D_n are the relative weight and nominal mean diameter of an armor block, respectively; N_0 is the number of blocks moving within the range of D_n ; N is the number of waves;

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