Wave Reflection at Submerged Breakwaters

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INTRODUCTION

Several types of structures are used in Coastal Engineering with the aim of preventing shoreline erosion, such as groynes, detached breakwaters, submerged breakwaters, etc. Submerged breakwaters have the advantage of their minimal visual impact, which has made them ever more popular (Chang & Liou, 2007).

When the incoming waves impinge on a submerged breakwater, a process of energy transformation occurs. Many laboratory and numerical studies have been carried out in order to investigate this process (Kobayashi & Wurjanto, 1989) (Losada, Losada & Martin, 1995) (Losada, Silva & Losada, 1996) (Liu, Lin, Hsu, Chang, Losada, Vidal & Sakakiyama, 2000). The energy of the incident wave is transformed as follows: (i) one part of this energy is transmitted above the crest of the structure and — in the case of permeable submerged breakwaters — through its interior; (ii) another part is dissipated by wave breaking and by friction with the structure during the transmission process and finally, (iii) the remaining energy is reflected seaward.

The reflection level is related with the scour in front of the structure. Therefore, a good knowledge about the reflection process may be helpful in order to avoid or at least mitigate the possible problems in the structure foundations. However, due to the complexity of the problem, the influence of all the relevant parameters (the structure slope and submergence, the water depth, the wave period and height, etc.) is not entirely understood yet and new approaches are needed.

In this work, an Artificial Neural Network (ANN) has been applied to a series of results obtained from a previous study of Taveira-Pinto (2001), in which several physical models were tested. Once trained and validated, the ANN has been used to estimate the wave reflection coefficient.

BACKGROUND

ANNs have proved to be a very powerful and versatile Artificial Intelligence technique (Orchad, 1993) (Haykin, 1999). In fact, they have been successfully applied to a great number of areas, including system identification and control, pattern recognition, data processing, time series prediction, modelling, etc (Rabuñal, Dorado, Pazos, Pereira & Rivero, 2004) (Rabuñal & Dorado, 2005).

In Civil Engineering, ANNs have been used most notably in Hydrology (Govindaraju & Rao, 2000) (Maier & Dandy, 2000) (Dawson & Wilby, 2001) (Cigizoglu, 2004). With regard to Ocean Engineering, ANN's have been applied to breakwater stability (Mase, Sakamoto & Sakai, 1995) (Medina, Garrido, Gómez-Martín & Vidal, 2003) (Kim & Park, 2005) (Yagci, Mercan, Cigizoglu & Kabdasli, 2005), wave forecasting (Tsai, Lin, & Shen, 2002) and tide-forecasting (Lee & Jeng, 2002).

ESTIMATION OF THE REFLECTION COEFFICIENT AT SUBMERGED BREAKWATERS

ANN Model

An Artificial Neural Network (Lippmann, 1987) (Haykin, 1999) is an information-processing system

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consisting of an interconnected group of many simple process elements. These elements, also called neural units or neurons, work together in a similar way as biological neurons in the brain. The input is presented to the input neurons and propagated through the whole network until eventually some kind of output is produced.

In this work, a FeedForward Backpropagation network (FFBP) has been used. FFBP networks are composed of different layers of neurons linked by means of feedforward connections and trained by a back-propagation algorithm. Feedforward means that the output of a given neuron is used as the input of to the following layer, so there are no feedback loops. In this case, a network with two neuron layers, a logarithmic sigmoid hidden layer and a linear output layer, has been adopted.

The adjustment of the network weights in order to reduce the error is carried out by means of the back-propagation algorithm (Freeman and Skapura, 1991; Johansson et al., 1992). The error, *i.e.*, the difference between the network output and the target (the expected output) is propagated through the network backwards, up to the input layer; all the while the weights are tweaked. This process is repeated over and over until either the error is lower than a threshold or a maximum number of iterations are reached.

The ANN was trained by means of the Bayesian Regularisation method (MacKay, 1992), known to be effective in avoiding overfitting.

Experimental Set Up

The data used for training and testing the ANN were obtained in laboratory tests of submerged breakwaters (Taveira-Pinto, 2001), carried out in the unidirectional wave tank of the Hydraulics Laboratory of the Faculty of Engineering of the University of Porto. The wave tank is 24.5 m long and 4.8 m wide with a maximum water depth of 0.40 m at the test section. The wave generator is a piston-type paddle, capable of generating regular and irregular waves. At the opposite end, a wave-absorbing gravel “beach” with a slope ratio of 1:20 was used in order to minimize the wave reflection level in the tank.

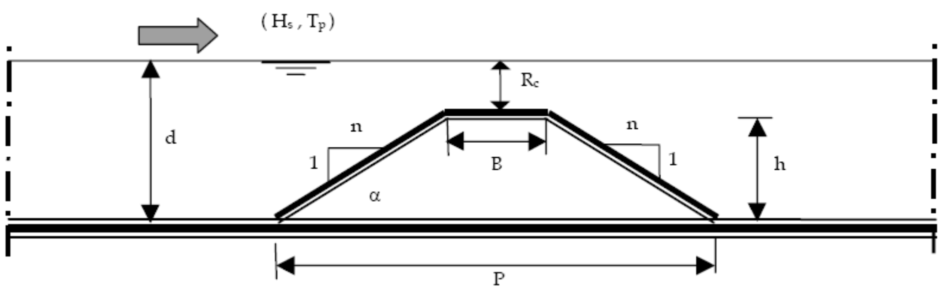
Six different impermeable models, constructed with wooden panels, were tested with different geometries (Fig. 1) at a 1:100 scale. Model height (h) was equal to 0.20 m in all cases (20 m in prototype). Different slopes (1:n) from 1:1 to 1:5 and two different crest widths (B), 0.05 m and 0.10 m, were tested.

Water surface displacements were measured using twin wire conductivity wave probes placed at different points in the wave tank. In order to evaluate the reflection coefficient (R), three wave probes were located on a line parallel to the wave direction. The spectral analysis method (Gilbert & Thompson, 1978), based on the Kajima (1969) method, was used to separate the incident and the reflection components.

A total of 275 tests were conducted with different water depths and irregular wave conditions. Water depths (d) between 0.20 m to 0.215 m, leading to freeboards (R_c) in the range 0 m to –0.015 m (negative for the breakwater crest below the still water level) were used during the tests. Irregular waves were generated conforming to the JONSWAP spectrum. Significant wave heights (H_s) from 2 cm to 8 cm and peak wave periods (T_p) from 0.8 s to 1.25 s were tested.

In order to carry out the training and the testing process of the ANN, the data were randomly divided

Figure 1. General layout of the testing models



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