Artificial Intelligence and Rubble–Mound Breakwater Stability

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INTRODUCTION

Breakwaters are coastal structures constructed to shelter a harbour basin from waves. There are two main types: rubble-mound breakwaters, consisting of various layers of stones or concrete pieces of different sizes (weights), making up a porous mound; and vertical breakwaters, impermeable and monolythic, habitually composed of concrete caissons. This article deals with rubble-mound breakwaters.

A typical rubble-mound breakwater consists of an armour layer, a filter layer and a core. For the breakwater to be stable, the armour layer units (stones or concrete pieces) must not be removed by wave action. Stability is basically achieved by weight. Certain types of concrete pieces are capable of achieving a high degree of interlocking, which contributes to stability by impeding the removal of a single unit.

The forces that an armour unit must withstand under wave action depend on the hydrodynamics on the breakwater slope, which are extremely complex due to wave breaking and the porous nature of the structure. A detailed description of the flow has not been achieved until now, and it is unclear whether it will be in the future in view of the turbulent phenomena involved. Therefore the instantaneous force exerted on an armour unit is not, at least for the time being, amenable to determination by means of a numerical model of the flow. For this reason, empirical formulations are used in rubble-mound design, calibrated on the basis of laboratory tests of model structures. However, these formulations cannot take into account all the aspects affecting the stability, mainly because the inherent complexity of the problem does not lend itself to a simple treatment. Consequently the empirical formulations are used as a predesign tool, and physical model tests in a wave flume of the particular design in question under the pertinent sea climate conditions are *de rigueur*, except for minor structures. The physical model tests naturally integrate all the complexity of the problem. Their drawback lies in that they are expensive and time consuming.

In this article, Artificial Neural Networks are trained and tested with the results of stability tests carried out on a model breakwater. They are shown to reproduce very closely the behaviour of the physical model in the wave flume. Thus an ANN model, if trained and tested with sufficient data, may be used in lieu of the physical model tests. A virtual laboratory of this kind will save time and money with respect to the conventional procedure.

BACKGROUND

Artificial Neural Networks have been used in civil engineering applications for some time, especially in Hydrology (Ranjithan et al., 1993; Fernando and Jayawardena, 1998; Govindaraju and Rao, 2000; Maier and Dandy, 2000; Dawson and Wilby, 2001; Cigizoglu, 2004); some Ocean Engineering issues have also been tackled (Mase et al., 1995; Tsai et al., 2002; Lee and Jeng, 2002; Medina et al., 2003; Kim and Park, 2005; Yagci et al., 2005). Rubble-mound breakwater stabil-

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ity is studied in Mase et al.'s (1995) pioneering work, focusing on a particular stability formula. Medina et al. (2003) train and test an Artificial Neural Network with stability data from six laboratories. The inputs are the relative wave height, the Iribarren number and a variable representing the laboratory. Kim and Park (2005) compare different ANN models on an analysis revolving around one empirical stability formula, as did Mase et al.'s (1995). Yagci et al. (2005) apply different kinds of neural networks and fuzzy logic, characterising the waves by their height, period and steepness.

PHYSICAL MODEL AND ANN MODEL

The Artificial Neural Networks were trained and tested on the basis of laboratory tests carried out in a wave flume of the CITEEC Laboratory, University of La Coruña. The flume section is 4 m wide and 0.8 m high, with a length of 33 m (Figure 1). Waves are generated by means of a piston-type paddle, controlled by an Active Absorption System (AWACS) which ensures that the waves reflected by the model are absorbed at the paddle.

The model represents a typical three-layer rubble-mound breakwater in 15 m of water, crowned at +9.00 m, at a 1:30 scale. Its slopes are 1:1.50 and 1:1.25

on the seaward and leeward sides, respectively. The armour layer consists in turn of two layers of stones with a weight W=69 g ±10%; those in the upper layer are painted in blue, red and black following horizontal bands, while those in the lower layer are painted in white, in order to easily identify after a test the damaged areas, *i.e.*, the areas where the upper layer has been removed. The filter layer is made up of a gravel with a median size D_{50} = 15.11 mm and a thickness of 4 cm. Finally, the core consists of a finer gravel, with D_{50} = 6.95 mm, D_{15} = 5.45 mm, and D_{85} = 8.73 mm, and a porosity n = 42%. The density of the stones and gravel is γ_r = 2700 kg/m^3.

Waves were measured at six different stations along the longitudinal, or x-axis, of the flume. With the origin of x located at the rest position of the wave paddle, the first wave gauge, S1, was located at x=7.98 m. A group of three sensors, S2, S3 and S4, was used to separate the incident and the reflected waves. The central wave gauge, S3, was placed at x=12.28 m, while the position of the others, S2 and S4, was varied according to the wave generation period of each test (Table 1). Another wave gauge, S5, was located 25 cm in front of the model breakwater toe, at x=13.47 m, and 16 cm to the right (as seen from the wave paddle) of the flume centreline, so as not to interfere with the video recording of the
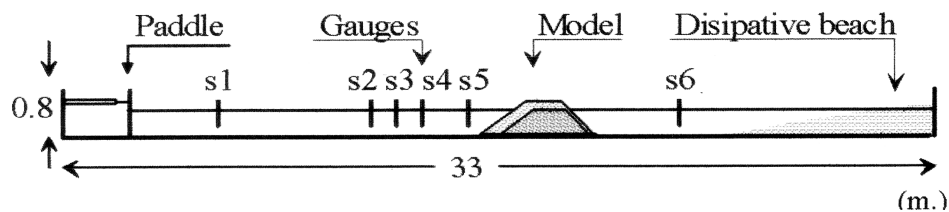
Figure 1. Experimental set-up

Table 1. Relative water depth (kh), wave period (T), and separation between sensors S2, S3 and S4 in the stability tests

Test key	*kh*	*T* (s)	S2-S3 (cm)	S3-S4 (cm)
T10, T20	0.98	1.65	35	55
T11, T21	1.36	1.3	20	30
T12, T22	1.68	1.13	20	30
T13, T23	1.97	1.03	20	30

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