Ocean Engineering 35 (2008) 1113–1120

Contents lists available at ScienceDirect

Ocean Engineering

journal homepage: www.elsevier.com/locate/oceaneng

A virtual laboratory for stability tests of rubble-mound breakwaters

G. Iglesias [a,*], J. Rabuñal [b], M.A. Losada [c], H. Pachón [b], A. Castro [b], R. Carballo [a]

[a] Department of Agroforestry Engineering, University of Santiago de Compostela, E.P.S., Campus Universitario s/n, 27002 Lugo, Spain
[b] University of A Coruña, CITEEC, Campus de Elviña s/n, 15192 A Coruña, Spain
[c] University of Granada, CEAMA, Avda. Mediterráneo s/n, 18006 Granada, Spain

A R T I C L E I N F O

Article history:
Received 12 October 2006
Accepted 27 April 2008
Available online 4 May 2008

Keywords:
Artificial intelligence
Artificial neural networks
Coastal engineering
Coastal structures
Breakwater
Armor damage

A B S T R A C T

The prediction of rubble-mound breakwater damage under wave action has usually relied on costly and time-consuming physical model tests. In this work, artificial neural networks (ANNs) are applied to estimate the outcome of a physical model throughout an experimental campaign comprising of 127 stability tests. In order to choose the network best suited to the problem data, five different activation function options and 38 network architectures are compared. The good agreement found between the physical model and the neural network shows that an ANN may well serve as a virtual laboratory, reducing the number of physical model tests necessary for a project.

1. Introduction

The most important mode of failure of rubble-mound breakwaters is removal of armor layer units by wave action (Bruun, 1985). A good design must ensure that under the worst expected storm waves, the number of armor units displaced by waves is low enough that breakwater collapse does not ensue, so that the damage can be duly repaired after the storm. As the stability of armor units is mainly assured by gravity, the determination of unit weight is a crucial step in the design process. Since the pioneering work by Iribarren (1938), several empirical formulae have been presented for this purpose, such as those of Hudson et al. (1979), Losada and Giménez-Curto (1979), or Van der Meer (1988). It is however all but impossible for a simple formula to fully account for the complex response of a rubble-mound structure in the face of storm waves—hence the need for hydraulic model tests in coastal engineering practice, with the eventual exception of minor structures. Such laboratory tests are costly and time consuming. In the present study artificial neural networks (ANNs; Lippmann, 1987; Haykin, 1999) are used to simulate the behavior of a model rubble-mound breakwater in a wave flume.

ANNs have already been used in ocean engineering, in particular to study rubble-mound breakwater stability. The application of Mase et al. (1995) centered around the empirical formula of Van der Meer (1988)—their ANN used the same parameters and was trained and tested on the data set that had served to develop the formula. Medina et al. (2003) used an ANN whose inputs were the relative wave height, the Iribarren number of the waves, and a variable representing the laboratory where the stability tests had been carried out, which eventually proved irrelevant. Kim and Park (2005) compared five different ANN models and showed that the ANN technique can yield better results than a conventional empirical model. Yagci et al. (2005) used various artificial intelligence techniques, including ANNs, characterizing the waves by their height, period, and steepness.

All these works have in common the application of multilayer feedforward networks trained with the backpropagation algorithm (Freeman and Skapura, 1991), usually known as feedforward backpropagation networks, to the problem of rubble-mound breakwater stability. An important difficulty when using this kind of model resides in the absence of rules to define the neural architecture (the number of neuron layers and of neurons in each layer) that will perform best in a given problem. It is shown in this work that the model's ability to simulate the breakwater response under wave attack may vary significantly between architectures; hence the decision as to which architecture to use should be based on a comparison of the performances of a number of reasonable options. However, the above-mentioned studies have used only one ANN, or a few at most. In this work, the performances of 38 different architectures of feedforward backpropagation networks, ranging from one to six hidden neuron layers, are compared. Moreover, as the results of a feedforward backpropagation model also depend on the activation functions used by the neurons to generate their output, five different combinations of activation functions are also compared.

* Corresponding author. Tel.: +34 982 285900; fax: +34 982 285926.
E-mail address: iglesias@usc.es (G. Iglesias).

0029-8018/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.oceaneng.2008.04.014

The main advantage of feedforward backpropagation networks lies in their generalization capabilities, meaning that they may be used to estimate the armor damage that a model breakwater will sustain under a given set of conditions even if these conditions were not part of the data set with which the network was trained. Yet, feedforward backpropagation networks are not without drawbacks; among them are the results' sensitivity to the initialization weights, which are randomly set at the beginning of the training process. This aspect has been mostly unattended in previous ocean engineering applications of this kind of ANNs. In this study, the spurious influence of the initialization values is avoided by training and testing each neural network 40 times, and averaging the results.

The Iribarren number of the waves determines the kind of breaking occurring on the breakwater slope, which in turn controls how the incident energy is expended, i.e. the balance between reflection, dissipation, and transmission to the leeward. Needless to say, this balance has a great effect on the hydrodynamics on the slope. For this reason the Iribarren number is included among the network inputs in this work, alongside the wave height, period and, last but not the least, the damage level of the structure prior to each wave run. If the ANN is to reproduce the behavior of a model breakwater, it should not be left without this piece of information, which is obviously available to the physical model.

2. ANNs

An ANN (Lippmann, 1987; Haykin, 1999) is an information-processing system based on generalizations of human cognition or neural biology. It consists of many simple computational neurons, also called neural units or process elements, connected to each other much in the same way as "real" (biological) neurons in the brain—hence its name. An input vector is presented to the input neurons and propagated through the whole network until eventually some kind of output is produced. The most common type of ANN—and the one used in this work—is the feedforward backpropagation network, which is composed of different layers of neurons intertwined through feedforward connections, meaning that the output of a neuron in a given layer cannot be input to neurons of the same or preceding layers. This kind of network is usually trained with the backpropagation algorithm (Johansson et al., 1992), a gradient descent technique based on the adjustment of the weights of the neural connections to minimize the error. First, the error is computed by comparing the expected output with that obtained for a certain set of input data. Second, the error is propagated backward from the last or output layer until the first or input layer, and the weights are adjusted in the process. This procedure is repeated over and over with the same set of data (known as the training data) until either an error threshold or the maximum number of iterations is eventually reached. Finally, the ANN is tested for validation with a different set of data (the testing data).

Although in principle neurons may use any differentiable function as transfer or activation function, the most common functions in backpropagation networks are the log-sigmoid, tan-sigmoid, and linear transfer functions:

$$y = \mathrm{logsig}(x) = \frac{1}{1+\exp(-x)}, \tag{1}$$

$$y = \mathrm{tansig}(x) = \frac{2}{1+\exp(-2x)} - 1, \tag{2}$$

and

$$y = \mathrm{lin}(x) = x. \tag{3}$$

With one or more hidden layers consisting of sigmoid neurons and a linear output layer, the ANN can approximate any function with a finite number of discontinuities. If the linear output layer is dispensed with, the network output will be limited to the interval $(0, 1)$ or $(-1, 1)$, in the case of log-sigmoid or tan-sigmoid neurons, respectively.

3. Experimental data

The data for training and testing the ANNs were obtained from stability tests of a model rubble-mound breakwater. The experimental setup and the testing procedure are briefly described hereafter. A detailed description was reported in Iglesias et al. (2003).

The stability tests were carried out in a wave flume at the CITEEC laboratory of the University of A Coruña, Spain. The flume is 33.8 m long, 4 m wide, and 0.8 m deep (Fig. 1). The wave generator is a piston-type paddle capable of generating regular and irregular waves, and equipped with active absorption of reflected waves. A wave-absorbing gravel "beach" is located at the downwave end of the flume. It is 7 m long, with a parabolic profile culminating at a height of 0.55 m above the flume bottom. Prior to the model breakwater's construction, reflection tests were performed with waves of different heights and periods; the reflection coefficients were below 0.1 (10%) in all cases tested.

The model section of the flume was divided into three longitudinal strips, henceforward known as subflumes, by means of vertical wooden panels parallel to the flume axis (Figs. 1 and 2). This division not only enabled three tests to be performed simultaneously but also prevented the generation of spurious transversal oscillations due to the reduced width of the subflumes. The lateral subflumes were 1.5 m wide, with an effective model width of 1.0 m, while the central subflume was 1.0 m wide.

Three model breakwaters of identical cross-section were constructed in the three subflumes. The model breakwater section consisted of a core, a filter layer, and an armor layer (Fig. 3), representing a typical breakwater in 15 m of water at a 1:30 scale. The crown height of the model breakwater was sufficient to prevent wave overtopping under the wave conditions tested (see below). The core material was fine gravel with a median size $D_{50} = 6.95$ mm. The filter layer was made up of coarser gravel, $D_{50} = 15.11$ mm, with characteristic weights $W_{50} = 9.3$ g, $W_{15} = 5.6$ g, and $W_{85} = 14.5$ g. The armor units were angular stones weighing $W = 69\,\mathrm{g} \pm 10\%$ (nominal diameter $D_\mathrm{n} = 2.95$ cm), with the armor layer consisting of two layers of units. The stones in the upper armor layer were painted in three horizontal stripes of blue, red, and black, so that a displaced stone could be ascribed to a part of the armor layer; those in the lower layer were painted in white, so that the vacuum left in the upper layer by a removed stone would stand out on a slope photograph.

Water surface elevation was measured at 10 points in the flume using twin wire conductivity wave gauges. Each subflume was instrumented with a group of three wave gauges aligned perpendicular to the face of the model breakwater (Figs. 1 and 2), with the central gauge of the group at a distance of 1.36 m from the structure toe; the distances of the other two gauges were varied according to the wave period of the test. Finally, a gauge was installed on the flume centerline at a distance of 3 m from the wave paddle. The sampling rate was 20 Hz, and data acquisition was synchronized with the start of wave generation. The method of Baquerizo (1995) was used to estimate the reflection coefficient for each test from the wave gauge records. Based on the free surface displacements measured at three nearby points aligned with the wave direction, the method relies on a least squares technique to separate the incident and reflected waves and