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A 3D numerical model of nearshore wave field behind submerged breakwaters

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ABSTRACT

The functional design of submerged breakwaters is still developing, particularly with respect to modeling of the nearshore wave field behind the structure. An effective design tool needs to calculate both 2D and 3D effects. A numerical method for predicting the spatial transmission coefficient for regular waves in the shadow region of a 3D submerged breakwater is proposed in this paper. Two distinct models have been developed using machine learning algorithms; these artificial neural networks, based on multi-layer perceptron (MLP) and radial-basis function (RBF) methods, have been designed and trained against new laboratory experimental data expressed in terms of both dimensional and non-dimensional parameters. Comparisons between the experimental data and predictions from the trained models show that the non-dimensional RBF model is able to best predict the 3D wave field around the submerged breakwater. The performance of the model was validated in interpolation, extrapolation and at larger scale using different laboratory facilities, revealing sufficient agreement with the experimental results to suggest that it has potential as a design tool in real applications.

1. Introduction

Wave-generated turbulence, surge and currents created in the surf zone as the result of wave breaking cause sediment transport and consequently shoreline erosion and accretion. Because of population growth in coastal areas as a result of urban development and recreational activities, shoreline erosion has emerged as a serious concern. Various coastal defense structures such as dikes, revetments, seawalls, and emerged or submerged breakwaters are often adopted to protect the shoreline either by stopping waves reaching the shoreline or at least forcing them to break and to some extent dissipate their energy. Among these structures, submerged breakwaters are increasingly preferred due to lower construction costs and the significant dissipation of incident wave energy in the sheltered area leeside of the breakwater in an environmentally friendly way. Retaining a clear view of the sea, preserving alongshore transport and maintaining high water quality leeside are the additional key features of submerged breakwaters. Constructing submerged breakwaters is intended to reduce erosion, trap natural sediments and restore beaches. However, shoreline response to submerged breakwaters is particularly influenced by the nearshore circulation and wave field behind the structure driven by both 2D and 3D coastal processes such as permeability through the body (2D), wave overtopping over the crest (2D) and diffraction through the heads (3D).

2D wave transmission has been widely studied. Wave transmission coefficient K_t defined as the ratio of transmitted to incident wave height is widely used by researchers to study the wave transmitted behind coastal structures. Several different 2D design tools have been proposed to calculate K_t behind 2D submerged breakwaters: (Buccino and Calabrese, 2007; Calabrese et al., 2002; d'Angremond et al., 1996; Goda and Ahrens, 2008; Panizzo and Briganti, 2007; Seabrook and Hall, 1998; van der Meer et al., 2005). However, the only information provided by these models is the average value of K_t rather than the spatial distribution of wave height required of a reliable and accurate engineering design tool. What is required is a method of predicting wave diffraction around the head of the structure combined with the wave dissipation by overtopping. Very few studies on the 3D effects (Bellotti, 2004; Caceres et al., 2008; Hur et al., 2012; Johnson et al., 2005) and even fewer on combined diffraction and overtopping effects of similar structures have been conducted in the past (Buccino et al., 2009; Losada et al., 1996; Vicinanza et al., 2009). The majority of these studies are restricted to low-crested structures with a small number considering fully submerged breakwaters. This was the stimulus for the present study, which is intended to improve nearshore wave field modeling around submerged breakwaters with particular emphasis on flow circulation and associated sediment transport.

The spatial distribution of the nearshore wave field around submerged breakwaters has been investigated numerically using data-driven algorithms called Artificial Neural Networks (hereafter ANNs). Such models have proved to be useful in many fields of engineering to solve complicated nonlinear problems where many relationships are involved. ANNs have actually been applied successfully to some coastal engineering problems (Mase et al., 1995; Medina, 1999; Panizzo and Briganti, 2007; van Gent and van den Boogard, 1998; van Gent et al., 2007; van Oosten et al., 2006).

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In the present study, two different ANN models have been designed and trained using new experimental data and the predicted transmission coefficients compared against each other and against actual data measured in facilities of different size.

The main body of the paper is divided into six sections. The introduction offers an overview of the topic, justification for the study, and a brief literature review. Section 2 presents a brief description of artificial neural network models and the basic concepts including an explanation of the specific neural network models used in this study. A description of the experiments, the methods of data selection, and approaches for data pre-processing to prepare the training data are set out in Section 3. An investigation of existing design tools is presented in Section 4. Section 5 concerns the numerical modeling using ANNs created specifically in this project including the ANN model setup, calibration, analysis of the model performance and verification. The capability of the proposed numerical models to simulate wave height transformation over submerged breakwaters is investigated in Section 6. ANN models are tested in the numerical simulations and the results compared to the laboratory experimental data. And finally, Section 7 completes the paper with the main conclusions.

2. Artificial neural networks

Artificial neural networks imitate the structure of biological neural networks. They consist of a massive number of computational units simulating neurons (acquiring knowledge) and connected together with interconnection weights which simulate synapses (storing the knowledge) (Haykin, 1999). Through a learning process, network parameters such as interlayer weights and bias values are modified and adapted. Depending on how the ANNs are applied, the learning process employed can be classified as supervised or unsupervised. Basically, supervised learning is suitable for function estimations when input–output paired data and a mathematical method for the learning process are available, while unsupervised learning may be best in the case of pattern recognition using data without a target (Haykin, 1999). In this research, we are dealing with a function estimation problem; therefore supervised learning is considered appropriate and will be discussed further. For more information about other learning methods and unsupervised methods in particular, please see: Haykin (1999). In engineering applications, the most popular artificial neural network is the multi-layer perceptron (MLP). Radial basis function (RBF) networks with universal non-linear approximation properties are similar to multi-layer perceptron in that they also use memory-based learning algorithms for their design (Haykin, 1999; Park and Sandberg, 1993). An introduction to ANN models, their basic framework, theoretical properties, and differences between the ANN models employed in this paper, are set out below.

2.1. Multi-layer perceptron (MLP) network

A multi-layer perceptron has an input layer, one or more hidden layers and an output layer of computation units named neurons. The transfer function of a multi-layer perceptron computes the inner product between the input vector and the corresponding inter-layer weight vector. Using a supervised form of learning for a given training data set S including n input–output pairs, the learning algorithm computes weights and biases of the network, so that the mean-square error (MSE) is minimized (Haykin, 1999):

$$S = \{(x_i, y_i)\}, i = 1, \ldots, n \tag{1}$$

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n} [y_i - \widehat{y}_i]^2}{n} \tag{2}$$

where x_i, y_i and y_i are respectively input, target response and output computed by the network for the ith sample.

A back-propagation (BP) algorithm (Rumelhart et al., 1986; Werbos, 1988) is usually employed to train MLP networks. The BP algorithm initializes the network parameters, propagates the input data forward through the network, and computes the output error as (Haykin, 1999):

$$e_i = y_i - \widehat{y}_i. \tag{3}$$

The computed error e_i is then propagated backward through the network and the weights and biases are adjusted so as to minimize the mean-square error. Dealing with a nonlinear regression problem, batch mode is implemented to adjust the network parameters in BP learning on an epoch by epoch basis where each epoch consists of the entire set of training samples (Haykin, 1999). Although simplicity and efficiency in computations are significant advantages of BP learning, limitations on convergence and slow learning speed, which is even more annoying when complexity increase, is a disadvantage of the algorithm. For more information about MLP networks and BP algorithm, please see: Haykin (1999).

2.2. Radial-basis function (RBF) network

The RBF neural network concept was introduced by Broomhead and Lowe (1988). Comparable to a MLP network, for the RBF network the entire data set is split into two main data sets and exploited by two distinct procedures of training and testing. The training process in RBF can be interpreted as a curve-fitting problem, to find a surface in multi-dimensional space which provides a best fit to the training data set. The testing process, known also as generalization, is to use this multi-dimensional surface for interpolating the test data set (Broomhead and Lowe, 1988; Poggio and Girosi, 1990).

A RBF network consists of an input layer utilized to feed the input data into the network, a hidden layer to compute the outcome of the radial-basis functions and an output layer to combine the outputs from the radial-basis linearly. The outcomes of the input layer are calculated based on the Euclidean distance between the network input vector and RBF unit's center vector c. The hidden layer is a linear combination of basis functions and outputs of this layer that are weighted forms of the input layer outputs. A general expression of the network can be presented as (Robert and Howlett, 2001):

$$y(x) = \sum_{k=1}^{m} w_k \Phi(\|x - c_k\|) + b \tag{4}$$

where $w_1, w_2, \ldots, w_m$ are weight factors, Φ is the hidden layer transfer function, c_k is the center vector of the kth RBF unit and b is bias value.

The most popular and widely used radial basis function is Gaussian:

$$\Phi(\|x - c_k\|) = e^{-\left(\frac{\|x - c_k\|^2}{2\sigma_k^2}\right)} \tag{5}$$

where σ_k is the width of the kth RBF unit, a positive real number known also as the scaling parameter.

3. Data collection

This section describes preparation of the experimental data set used in this study to train and test the ANN models. Preparing data in ANN modeling is an essential stage. For an accurate prediction, data preparation should be undertaken firstly to speed up the training process, secondly to reduce the model complexity, and thirdly to increase its scope for generalization. Therefore, achieving success in ANN modeling depends critically on this stage and requires that the ANN is trained using high quality data. In the present study, a large number of 3D experiments have been conducted in wave tanks in the presence of