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Machine learning based prediction of wave breaking over a fringing reef

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ABSTRACT

The characteristics of wave breaking in shallow waters that are of interest include whether a wave will break, the type of breaking that will occur, the breaking wave height, breaking depth, the position of breaking, the wave setup, and the transformation of the broken wave for given offshore wave characteristics and given bottom profile. Various methods have been proposed in the literature to estimate these wave-breaking characteristics. Deo et al. (2003) used a neural network approach to predict the breaking wave height and breaking depth for waves transforming over a range of simply sloped bottoms. The Deo et al. approach is extended here to predict other characteristics of wave breaking, including the type of wave breaking, the position of breaking, the wave setup, and the rate of dissipation of wave energy, in the case of waves impinging on a fringing reef. Observations from a series of specially conducted laboratory experiments involving monochromatic waves impinging on an idealized reef are used to develop and train respective models. The input parameters to the neural network models are the ratio of offshore wave height to the shallow-water depth of the flat section of the reef, H_1/h_s and the wave frequency parameter $f\sqrt{H_1/g}$. The breaker type classification model developed predicts the type of breaker with a success rate of 96%, outperforming previously used criteria for classifying breaker types. The numeric prediction models for the dimensionless position of wave breaking for plunging and spilling breakers, for wave setup, and for the reduction in energy flux across the reef have performance ratings characterized by respective correlation coefficients of 0.99, 0.82, 0.89, and 0.94. The modest value for the correlation between prediction and the actual result for the position of breaking of spilling breakers is believed to be associated with inaccuracies in determination of the exact position of breaking and to difficulty in visually capturing spilling breakers in observations. High correlation between predicted and actual values of the reduction in energy flux across the reef is achieved in spite of the fact the model was trained using data from a wave tank that included partial reflection (characterized by 7% mean deviation among non-breaking waves) from the downstream end of the tank. The method can be extended to provide predictive models for consideration of a range of natural coastal conditions, random waves, and various bottom profiles and complex geometry, based on training and testing of the models using representative laboratory, field, and/or flow simulation, in support of accurate prediction of near-shore wave phenomena.

1. Introduction

The propagation of ocean waves from deep to shallow water has received special attention from engineers and researchers, in view of the large amount of energy inherent in ocean waves. As a wave travels onshore, its characteristics are transformed, leading to increase in the wave steepness due to shoaling and the evolution of the energy distribution over the frequency spectrum (Goda, 1975). This energy can be impactful for nearshore structures or floating vessels. In such cases, it may be desirable to have the waves break upstream of the area to be protected, so that some of the wave energy is dissipated. That is why breakwaters are constructed to protect floating vessels and nearshore structures (Coastal Engineering Research Center, 1984). Another coastal problem, which is analyzed in (Coastal Engineering Research Center, 1984) and is related to breaking waves, is sediment mobilization and coastal erosion. A three-part work, presented in (Brocchini et al., 2004), (Kennedy et al., 2006), and (Piattella et al., 2006), deals with the breaking-wave-induced macrovortices. This work is based on

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experimental, computational and analytical methods, analyzing rip current effects and the mixing features of the shallow flows occurring around submerged structures used for coastal protection. In many cases, the natural environment can act as a breakwater where the main parameter of interest is the bottom profile. In designing coastal defenses and structures, it is necessary to predict the breaking wave characteristics of waves, including the location where they will break, the breaking wave height, the type of breaking that will occur, and the resulting wave setup.

The process of wave transformation and wave breaking is non-linear. Stokes, cnoidal and stream function theories are used to describe wave profiles preceding wave breakup (Dean and Dalrymple, 1991), (Dean, 1972), Wave evolution leading to wave breaking is typically followed numerically using methods based on the Boussinesq equations (Yao et al., 2012), (Peregrine, 1967). A Boussinesq model is derived in (Veeramony and Svendsen, 2000) for predicting breaking waves and has been extended in (Briganti et al., 2004) to incorporate turbulence associated with a breaking wave in the surf zone. The model proposed by Yao et al. in (Yao et al., 2012) for the wave profile is compared with their laboratory experiments (Yao et al., 2009).

Studies based on the assumption of planar beach profiles with mild constant slopes provide simplified (McCowan, 1894), (Goda, 1970), or more advanced breaking criteria (Weggel, 1972), (Goda, 2010), for the nearshore zone. A novel breaking index for fringing reefs extracted from laboratory experiments is provided in (Yao et al., 2013). Extensive research has been carried out to model the transformation of the wave height, $H(x)$, as well as the wave setup, $\overline{\eta}(x)$, for irregular bottom shapes. An approach based on an energy balance, and involving consideration of one-dimensional gradient of energy flux is sometimes used (see for example, (Dally et al., 1985), and (Kweon and Goda, 1996)). According to (Dally et al., 1985) and (Yao et al., 2012), the effect of bottom friction on the surf zone phenomena in fringing reef type profiles is negligible, but is important in regions of mild slopes.

Versions of the models of the type described above for wave transformation in the coastal region are used to account for various factors, including wind and offshore wave conditions, type of bottom profile, bottom material, and other features and processes. The models typically require empirically determined parameters, derived through statistical curve-fit to laboratory or field data. Simple empirical criteria such as the wave height-to-depth ratio criterion for wave breaking, are used under some conditions, with the breaking position measured from the shore typically obtained from the ratio of the depth at breaking to the beach slope (Dean and Dalrymple, 1991). Similarly the surf similarity parameter is an empirically derived index to classify the breaker type as a function of the bottom slope and breaking wave steepness (Battjes, 1974). The criteria in both cases are provided for planar beach profiles with mild constant slopes. An extensive experimental study to judge and compare the validity of various criteria including breaking type classification, breaking location, surf zone width and the incipient breaker height and depth indices is considered in (Yao et al., 2013).

Modern machine learning techniques have been proposed during the last decade, incorporating data mining algorithms (Witten et al., 2011) to train models that can provide good empirical models. The concept of a neural network (NN) for wave forecasting was introduced by Deo et al. in (Deo and Naidu, 1999) and (Deo et al., 2001). The idea was extended to prediction of the wave height and depth at wave breaking (Deo and Jagdale, 2003), using, a NN model that was trained based on classic criteria for wave breaking provided in (Coastal Engineering Research Center, 1984) and validated using several experimental data sets over a broad range of conditions.

Here, predictive neural network models for parametric characterization of wave breaking over a fringing reef in the coastal region for given offshore wave characteristics and bottom geometry are developed, based on the machine learning concept and laboratory experiments. The characteristics considered include classification of the type of wave breaker, the position of wave breaking, the wave setup downstream of position of breaking and the rate of dissipation of wave energy during breaking. The machine learning technique that is chosen is the multilayer perceptron which is a type of feedforward artificial NN (Baum, 1988). The networks are trained using observations from laboratory experiments. The models for the wave characteristics are distinguished (see (Witten et al., 2011)) as: the classification model, as providing prediction for data available in non-numeric or nominal value form (such as spilling, plunging, or non-breaking waves); and numeric prediction models, as providing predictions for data available in numeric form (such as location of breaking, wave setup and energy flux). The proposed method is aimed to have the following advantages: (1) the method is oblivious to whether the underlying physical process is linear or nonlinear, with the multilayer perceptron accommodating possible nonlinear interactions that may characterize the physical processes through seeking a statistical relationship between the input parameters and the resulting observed data; (2) a matrix formulation expresses the NN in a compact form; (3) it facilitates simple extensions of the training of the models through use of larger or more representative datasets for improvement and development of robust models; (4) it facilitates consideration of a variety of realistic features which may be difficult to model theoretically (e.g. offshore wind or current characteristics, bottom material, etc.) through expansion of the input attributes via a new training procedure that generates a fresh model; (5) datasets can be generated from laboratory or field experiments or numerical simulations, or their combination; (6) evaluation and improvement of the model is achieved through field or laboratory experiments; (7) nominal or non-numeric attributes can be included in the form of representative integer numbers. The limitations of the method include 1) the model is based on range of the data set used for training the model, 2) a good distribution of samples in the training data set is required, and 3) a NN model does not provide a single regression equation relating inputs and outputs; instead the model serves as the equation for the relationship.

2. Matrix formulation of the neural network

The machine learning technique chosen to predict breaking wave phenomena is based on, a multilayer perceptron, a type of feedforward artificial NN (Baum, 1988). The networks are trained based on experimental datasets using a collection of open-source machine learning algorithms called Weka (Witten et al., 2011) that is typically used for data mining tasks. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. Specifically, a back-propagation algorithm of the Weka tool is utilized here. Details regarding multilayer perceptrons and the training procedure are provided in (Witten et al., 2011). A compact mathematical formulation is presented in this section. According to the multilayer perceptron concept, three types of layers are identified: the input, the hidden and the output layers. The input and output are single layers while the hidden layer can be single or multiple. The following definitions, along with the diagram in Fig. 1, establish the infrastructure for a compact description of the NN based on a matrix notation. The notation is defined below:

$i = 1, \dots, m$ hidden layer index
$j = 1, \dots, k_m$ node index
m number of hidden layers
k_i number of nodes at layer i
k_0 number of attributes
k_{m+1} number of output nodes
$\boldsymbol{a}$ $k_0 - by - 1$ attribute vector
$\boldsymbol{x_i}$ $(k_{i-1}+1) - by - 1$ input vector at hidden layer i
$\boldsymbol{s_i}$ $k_{i-1} - by - 1$ output vector at hidden layer i
$\Lambda(\boldsymbol{u})$ transformation operation for an $n - by - 1$ vector $\boldsymbol{u}$ to an $n - by - n$ diagonal matrix
$\boldsymbol{W_i}$ $k_i - by - (k_{i-1}+1)$ weight matrix at layer i