Ocean Engineering 109 (2015) 298–308

Contents lists available at ScienceDirect

Ocean Engineering

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

Artificial neural networks applied to port operability assessment

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ARTICLE INFO

Article history:
Received 30 April 2015
Accepted 10 September 2015
Available online 29 September 2015

Keywords:
Port of Ferrol
Wave agitation
Harbour tranquillity
Port operability
Artificial intelligence
Artificial neural network

ABSTRACT

Waves are one of the main factors that can disturb port operations, from berthing to cargo loading and unloading. Wave heights within port basins are typically assessed by means of numerical models based on the outer (offshore) wave conditions, the bathymetry and the port layout. The aim of this work is to implement an artificial neural network (ANN) model which, upon training and validation, will be capable of determining wave agitation within a port basin based on deep-water wave buoy observations alone. In the training the ANN model acquires knowledge on the problem from a series of examples, and thereafter applies this self-acquired knowledge to other (new) cases. To select the ANN architecture most appropriate for this task a comparative study involving 65 options is carried out using the *k*-fold cross-validation technique. Upon validation, the ANN model is used to carry out a sensitivity analysis in which the influence of the different input variables on the wave parameters in the basin is quantified. Finally, the model is applied to a case study—the Exterior Port of Ferrol—in order to evaluate wave agitation inside the basin and its influence on port operations.

1. Introduction

One of the main functions of a harbour is to provide safe anchorage for vessels in order to facilitate the loading and unloading operations of cargo and passengers (Goda, 2002). To perform these functions, the weather conditions inside the basin (wind, currents and, importantly, waves) must not exceed certain thresholds, which depend on the type of operation (mooring, loading or unloading) and cargo involved (Elzinga et al., 1992; PIANC, 1995; Puertos del Estado, 1999). Among the different weather elements affecting port operations, wave height inside the basin is one of the sources of most of the inoperative hours (Tsinker, 2004). It follows that knowledge of wave agitation in the basin is essential for the planning, design, construction, security and operation of ports. This is not, however, an easy task: as waves approach the coast, propagating from deep to shallow water, they interact with the seabed and shore through shoaling, refraction, diffraction, reflection and breaking. The ensemble effects of these phenomena change both the height and direction of waves, causing attenuation in some areas and concentration of energy in others.

In general, to assess the wave height inside a basin, the use of experimental or numerical models is required. Physical (or experimental) models could in principle be seen as one of the best alternatives; nevertheless, they have numerous drawbacks: they are expensive and time-consuming, and subject to laboratory and scale effects. Numerical models provide an approximate solution of the differential equations describing wave propagation. There are fundamentally two types of models: spectral models, which provide a phase-averaged description of wave propagation, e.g., SWAN (Rusu and Guedes Soares, 2011, 2013); and phase-resolving models, including mild slope models (Chen et al., 2005; Hamidi et al., 2012) or Boussinesq models (Bruno et al., 2009; Su et al., 2015). The main advantage of spectral models is that they consider the generation and development of wind waves; on the flip side, they cannot resolve phenomena like diffraction or reflection for which the phase information is essential. On the contrary, the mild slope and Boussinesq models do resolve the phase, but can only be implemented in small areas given their high computational cost. In all cases, wave observations from buoys or pressure gauges within the basin are recommended for validation.

This study proposes an alternative method based on artificial intelligence (AI), in particular, artificial neural networks (ANNs). Over the last few years, ANNs have been successfully applied to different ocean and coastal engineering studies, including the reliability of coastal structures (Iglesias et al., 2008; Kim et al., 2014), tidal prediction (Chang and Lin, 2006; Lee, 2004), long-wave prediction (López and Iglesias, 2013), wind direction forecasting (Tagliaferri et al., 2015), wave forecasting (Deo et al., 2001; Kashikar and Mane, 2014; Makarynskyy, 2004; Vimala et al., 2014) or beach morphology (Hashemi et al., 2010; Iglesias et al., 2009b). There are also several studies addressing the

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http://dx.doi.org/10.1016/j.oceaneng.2015.09.016
0029-8018/

assessment of harbour tranquillity (Kankal and Yüksek, 2012; Londhe and Deo, 2003). Nevertheless, these previous attempts rely on physical experiments and numerical model tests to train and validate the ANN, so do not suppose an alternative to the conventional models. The ANN model implemented in this work estimates the short-wave height inside a harbour from deep-water buoy observations, and, from the knowing of the limiting operational conditions, enables the assessment of port operability. The ANN is trained and validated based on field observations from wave buoys, making use of the same input data than conventional models do. However, the ANN adds a significant advantage over these models: it is several orders of magnitude faster than a conventional model, allowing studying the whole set of wave conditions and not only the most representative cases.

The methodology is illustrated through a case study: the Exterior Port of Ferrol (Galicia, NW Spain). It is a new basin located in the entrance of Ría de Ferrol (43.467°N, 8.334°W) (Fig. 1). It constitutes a very interesting case study because joins three main characteristics: (i) as an outer port it is much more exposed to wave action than the traditional ones; (ii) its large size, too much large to be modelled by a phase-resolving numerical model (which are compulsory for a harbour where diffraction is the dominating phenomenon), and (iii) a container terminal will soon be inaugurated (a traffic with a particularly high susceptibility to wave height disturbances).

2. Materials and methods

2.1. Artificial neural networks

An ANN consists in a set of highly interconnected elements, so-called neurons, working in parallel (Haykin, 1999; Jang et al., 1997; Nørgaard et al., 2003). ANNs, as a part of AI applications, emulate the behaviour of biological neural networks and, like them, their main characteristic is the adaptive learning, i.e., tasks are not required to be programmed, an ANN learns from experience. Furthermore, ANNs have also capacity to generalise from previous examples or to abstract the main characteristics of data series.

As aforementioned, the ANNs are composed of simple processing nodes called neurons. The artificial neurons receive a number of inputs and process them to produce the output: each input is multiplied by a weight, reinforced by a bias and the result is computed by a transfer function (also known as activation function) to delimit the output. The process of adjusting the value of the weights and biases to model the data is referred to as training or learning. In addition, using a learning algorithm, ANNs are able to adjust these parameters themselves. In order to provide an independent measure of how well the ANN responds another set of examples that have not been used to train is also needed, called validation set.

For this work, multilayer feed-forward back-propagation neural networks (hereafter, for the sake of brevity, back-propagation neural networks) were chosen on account of their generalisation capabilities (Hagan et al., 1996), which has been shown in a number of applications (e.g., Hashemi et al., 2010; Iglesias et al., 2009a; Kankal and Yüksek, 2012). This ability makes possible to train the ANN with only a representative number of cases and achieve good results in other totally new to the network. As its name suggests, back-propagation networks consist of several layers: an input layer, one or more hidden layers and an output layer. The number of neural layers and neurons per layer is referred to as ANN architecture. The training of these ANNs requires a set of examples—inputs and targets—, also known as training set, that shows the network which result it must obtain for a given input.

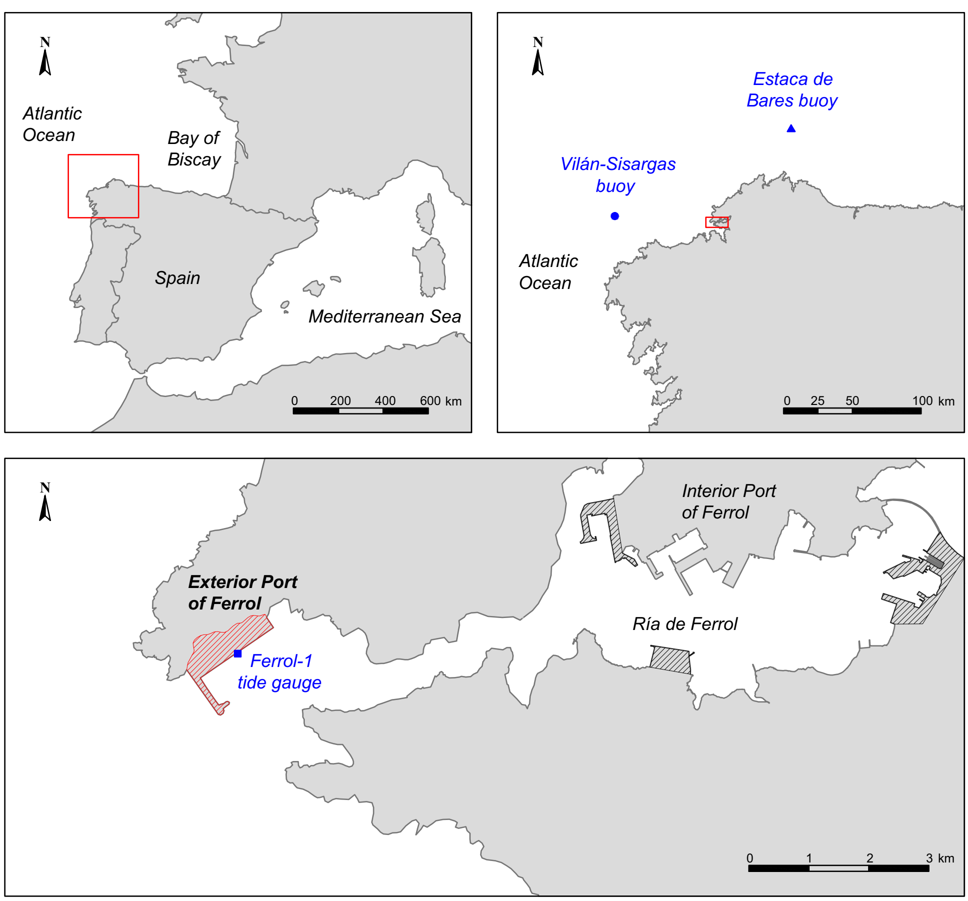

Fig. 1. Location of the Exterior Port of Ferrol, the Vilán-Sisargas and Estaca de Bares deep-water wave buoys and the Ferrol-1 tide gauge.