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Artificial Intelligence and headland-bay beaches

G. Iglesias [a,*], G. Diz-Lois [b,1], F. Taveira Pinto [c,2]

[a] Hydraulic Engineering, E.P.S., Campus Universitario, Univ. of Santiago de Compostela, 27002 Lugo, Spain
[b] Ports of Galicia, Area Central 10, 4°; Políg. Fontiñas, 15707 Santiago de Compostela, Spain
[c] Faculty of Engineering, University of Porto, Rua Dr. Roberto Frias, 4200-465 Porto, Portugal

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ABSTRACT

Headland-bay beaches are a typical feature of many of the world's coastlines. Their curved planform has aroused much interest since the early days of Coastal Engineering. Modelling this characteristic planform is a task of great interest, not least in relation to projects of coastal structures whose effects on the shoreline must be studied from the planning stages. In this work, Artificial Intelligence is applied to this task—in particular, artificial neural networks (ANNs). Unlike conventional planform models, they are not based on a given mathematical expression of the shoreline curve. Instead, they *learn from experience* (from a number of training cases) how the planform of a headland-bay beach is shaped, with due regard to the obliquity of incident waves. Three artificial neural networks, with different input/output structures, are implemented and subsequently trained with a number of bays. Once trained, they are tested for validation on other headland-bay beaches. Finally, the most performing neural network is compared with a state-of-the-art planform model.

1. Introduction

The curved planform of the beaches in the lee of natural headlands or breakwaters (e.g., Fig. 1), caused by wave diffraction and subsequent refraction, has aroused much interest since the early days of Coastal Engineering (Krumbein, 1947; Jennings, 1955; Davies, 1958; Silvester, 1960). Referred to as half-heart shaped bays (Silvester, 1960), crenulate-shaped bays (Ho, 1971; Silvester and Ho, 1972), spiral beaches (Le Blond, 1972), headland-bay beaches (Le Blond, 1979; Wong, 1981), static equilibrium bays (Hsu et al., 1989a,b), or bayed beaches (Tan and Chiew, 1994), the interest of their characteristic planform is not limited to the interpretation of existing coastal features. In effect, inducing the formation of new bays by means of artificial headlands can be used to control coastal erosion (Hsu et al., 1989c, 2008). With this in view, it is necessary to predict the planform which the shoreline will adopt on reaching equilibrium, be it dynamic or static (with or without sediment supply, respectively). Modelling the planform of headland-bay beaches is also important when a new coastal structure, e.g. a breakwater, is to be constructed on a sandy coast (Fig. 1). A curved shoreline will ensue, whose equilibrium shape must be determined beforehand as part of the environmental impact assessment of the project. Alternative layouts may thus be compared on the grounds of their impact on adjacent beaches.

Such tasks are usually carried out by means of empirical planform models. Among the first, Yasso's logarithmic spiral (1965) was a landmark work. Vichetpan (1969) and Silvester (1970a,b), among others, conducted further work on the logarithmic spiral model. Its practical application, however, is not without difficulty. Moreover, after some additional research it became clear (Hsu et al., 1987) that the logarithmic spiral did not provide a good fit to the complete shoreline curve of a headland-bay beach. To overcome this problem, Hsu and Evans (1989) put forward a new model in which the shoreline curve is expressed as a second-order polar coordinates. This *parabolic model* has found the widest application in Coastal Engineering practice. Tan and Chiew (1994) reduced the number of parameters in Hsu and Evans' (1989) model from three to one by imposing that the shoreline be tangent at the downcoast control point to the incoming wave fronts. González and Medina (2001) proposed a methodology to locate this control point, from which the parabolic model curve is applicable. Iglesias and Negro (2001) studied the influence on the bay planform of sediment supplies from small rivers or streams (dynamic equilibrium). Iglesias et al. (2002) put forward a planform model for the case of multiple diffractions.

In this work, an Artificial Intelligence tool, artificial neural networks (Lippmann, 1987; Haykin, 1999), is proposed to model the planform of headland-bay beaches. Although the objective is the same of conventional models, the approach is very different—to begin with, artificial neural networks (ANNs) are not based on a given mathematical relationship of the beach planform. Instead, they are capable of *learning from experience*, i.e. from a number of training cases. Indeed, the training

* Corresponding author. Tel.: +34 982 28 59 00.
E-mail addresses: gregorio.iglesias@usc.es (G. Iglesias), gonzalo.dizlois.palomares@xunta.es (G. Diz-Lois), fpinto@fe.up.pt (F.T. Pinto).
[1] Tel.: +34 981 54 52 03.
[2] Tel./fax: +351 22 508 1952.

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Fig. 1. Headland-bay beach at Espasante (NW Spain).

of an artificial neural network has many common points with human cognition. When people see a cat, they recognize the animal not by thinking in terms of an explicit definition ("a small domesticated carnivorous mammal with soft fur, a short snout, and retractile claws", according to the Compact Oxford English Dictionary), but simply because they have seen cats before. Much in the same way, an artificial neural network need not resort to a mathematical relationship in order to know the shape of a headland-bay beach, once it has "seen" many of them in the training process. "Seeing" means acquiring not only the coordinates of a number of shoreline points, but also the basic data concerning the embayment, namely the direction of wave incidence, the position of the *point of diffraction* and that of the *downcoast control point* (defined hereafter). These are the same basic data invoked by conventional planform models.

Three artificial neural networks are implemented to model the planform of headland-bay beaches. All three belong to the same class of neural networks—backpropagation networks, which are best suited to this kind of problem in the light of their generalization capabilities. Although the three of them share the same number of neural layers and neurons, they differ in the way in which data are inputted and outputted.

The artificial neural networks are trained by presenting them with a number of headland-bay beaches (the training data set). Once trained, they are tested on other cases of headland-bay beaches (the testing data set) by providing them with the basic beach data and contrasting the shoreline they yield with the real one, obtained from aerial orthophotos. Finally, the best of the three neural networks is compared with a state-of-the-art planform model.

2. Data set

In order to train the artificial neural networks, it is important to work with as many cases of headland-bay beaches as possible. A small data set would result in a poorly trained network, and subsequently in bad test results. This is not to say, however, that any headland-bay beach should be used. In this respect, it is essential that the beaches selected to form the training and testing data sets be as homogeneous as possible from the standpoint of the physical processes affecting the shoreline planform, at least inasmuch as the eventual heterogeneities are not accounted for by the model variables. It would be unwise, for instance, to consider headland-bay beaches in dynamic equilibrium alongside others in static equilibrium, given that no variable regarding sediment transport is included in the present formulation.

Hsu et al. (1989a) and Hsu and Evans (1989) found that the planform of a bay in static equilibrium depends only on wave obliquity. Only such static equilibrium bays will be used in this study. Moreover, if the obstacle causing the waves to diffract and thereby the shoreline to curve is not a natural headland but a breakwater, it is of paramount importance that sufficient time has elapsed since its construction for the planform to have attained equilibrium. The shoreline of the selected beaches should also be free of rock outcrops, which would be a source of *noise* for the neural network. It is also desirable that tidal currents be negligible or nil in the bay, for the sake of homogeneity. For similar reasons, there should be a single point of diffraction—cases where multiple diffractions occur, for instance at a natural headland and subsequently at a breakwater, are excluded.

After analysing many headland-bay beaches on the Mediterranean coast of Spain, seventeen beaches were selected on these grounds (Table 1). The condition of negligible tidal currents is automatically fulfilled on this tideless coast. Great care was exercised in ensuring that the other conditions were similarly met, with special emphasis

Table 1
List of headland-bay beaches used in the study.

Beach name	Province	Data set	θ_0	ρ_0 (m)
Arenys De Mar	Barcelona	Train	44.9°	799.0
Vilanova y La Geltrú	Barcelona	Test	54.9°	262.6
Calafell	Barcelona	Train	36.6°	375.5
Castellón	Castellon	Test	48.4°	162.1
Chilches	Castellon	Train	48.0°	247.9
Las Villas	Castellon	Test	40.3°	314.5
La Oliva	Valencia	Test	54.9°	177.6
Playa Del Cura	Alicante	Train	60.7°	173.6
El Campello	Alicante	Train	54.5°	484.9
Sta. Pola	Alicante	Test	44.0°	257.5
Tómbolo Sta. Pola 1	Alicante	Train	41.6°	76.0
Tómbolo Sta. Pola 2	Alicante	Test	48.8°	86.3
Tómbolo Sta. Pola 3	Alicante	Train	53.7°	69.7
La Mena	Almeria	Train	54.4°	93.6
Torreguardiaro	Cadiz	Train	60.1°	532.8
Peguera	Mallorca (Bal. I.)	Test	56.7°	220.1
Palma	Mallorca (Bal. I.)	Train	60.4°	312.8