Elsevier Editorial System(tm) for Ocean Engineering

Manuscript Draft

Manuscript Number: OE-D-15-01025R1

Title: NEURAL NETWORK FOR DETERMINING THE CHARACTERISTIC POINTS OF THE BARS

Article Type: Full length article

Keywords: sand bar beaches; artificial neural networks; precision profiles

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NEURAL NETWORK FOR DETERMINING THE CHARACTERISTIC POINTS OF THE BARS

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ABSTRACT

This article focuses on the optimal architecture of the neural network for determining the three characteristic points of the bars (starting, crest and final point). For the definition of the network, precision profiles, sedimentological and wave data were used. A total of 209 profiles taken for 22 years was used. The inputs were analysed and selected considering the variables that influenced the formation of the bars and their movement.

For the selection of the optimal model different architectures were studied, generating 50 models for each of them and selecting with better results and with the smaller number of neurons in the hidden layer. To evaluate the performance of the model, various statistical errors were used (absolute error, mean magnitude of relative error and percentage relative error), with an average absolute error of 17.3 m in the distances to the coast and 0.26 m in the depths. The results were compared with equations currently employed (Table 1), which show that the errors generated by the ANN (Artificial Neural Network) are much lower (per example the MAPE committed by the proposed equation for distance to shore of the crest is 47%, while the ANN is made of 29%).

Keywords: *sand bar beaches; artificial neural networks; precision profiles*

1. INTRODUCTION

The sandbars are important morphological characteristics of the beaches, and changes in position and height of sandbars are the main cause of a variability profile (Lippmann and Holman, 1990). Bars affect the waves and currents near the coast, which result in sediment transport and morphological evolution, including erosion and accretion of beaches (Kuriyama, 2002).

The cross-shore movement of the bars is necessary for the artificial regeneration of beaches. Apparently, the cross-shore displacement of the nourished sand depends largely on the location of the nourishment within the active zone. Spanhoff et al. (2005) suggested that shore-face nourishments placed above the bars location, tend to remain in the same position; whereas, nourishments placed further offshore of this position tend to migrate onshore, until they reach this location. Finally, when the sand is placed in the trough between the middle and the outer bar, the trough is newly formed within some months and the sand from the nourishment is incorporated into the bar system, contributing to the formation of a higher onshore bar. Another important factor is to condition the transport of sediment and pollutants (Short et al., 1996) and also biota (Jumars and Nowell, 1984). During storms, waves breaking over the crest of the bar creates strong currents near the bottom directed offshore (undertow) and lead to the migration of the bar to the sea (Gallagher et al., 1998; Hoefel and Elgar, 2003; Ruessink et al., 2009; Thornton et al., 1996). The beaches eroded by storms, at least partially recover sediment transport and migration to ground rods using less energy (Aubrey, 1979; Elgar et al., 2001; Hoefel and Elgar, 2003; Ruessink et al., 2009).

Among the models needed for the evolution of the cross-shore profile (including bars) supported by field observations, the type of energy models grounded in sediment transport is highlighted (based on Bagnold (1966)). These relate sediment transport to the flow near the bottom. Thus, we find the model proposed by Thornton et al. (1996) which uses the measured velocities near the bottom for 10 days in a beach profile of Duck, North Carolina, to promote a model of energy transport. Gallagher et al. (1998) also tested the Bailard (1981) model using field data. Hoefel and Elgar (2003) showed that the addition of dependent transport of acceleration-asymmetry and the Bailard (1981) model led to accurate predictions of bar migrations both to the coast and to sea. Henderson et al. (2004) simulated the bar migration by combining measurements of the water velocity and a bottom boundary layer model for wave-induced sediment transport. Gallagher et al. (1998), Hoefel and Elgar (2003), Henderson et al. (2004) compared the results of its models with the data collected during the field experiment conducted in Duck94 (1994), where elevation data, pressure and currents were collected in nine profiles between the months of August and October (Birkemeier and Thornton, 1994).

Furthermore, various researchers have proposed more or less simple equations to determine the characteristic points of the bars (Table 1), such as the onset, peak and end of the bar, based on experiments conducted in flumes. Horikawa et al. (1973) proposed a simple expression to determine the distance from the crest of the bar to the shoreline, which depended on the steepness (H_o/L_o), the wavelength (L_o), the period (T) and the test duration (t). Meanwhile, Larson and Kraus (1989), studied the profiles of erosion and accretion and proposed a formula for the height of the crest and the volume of the bar using experimental data. Silvester and Hsu (1997) determined the parameters of the beach profile by non-linear regression techniques using various experimental data obtained from previous work.

Hsu (1998) after a series of experiments conducted using a three-dimensional model on a flume with moving bed, having two types of earrings, two angles of swell and different steepness of erosive waves, obtained a series of empirical relationships between characteristic geometric profile of a storm and the modified Iribarren number (Equation 1). This model includes the effects of the slope of the beach (m), the angle of incidence of the breaking wave (θ_b) and the steepness (H_o/L_o), where H_o and L_o are the height of wave and the wavelength in deep water respectively.

$$\xi_\theta = \frac{\mathrm{m}}{\sqrt{H_o/L_o}} \cos \theta_b \qquad (1)$$

More recently, Günaydın and Kabdaşlı (2005) also studied the parameters of the bar using physical models under conditions of regular and irregular wave flume. They determined the position of the bars using the obtubieron model parameters, related functions using linear regression techniques, and compared with other functions obtained using similar techniques.

Kömürcü et al. (2007) presented a series of equations to determine the position and depth of the ridge, the distance to break even (starting point of the bar and after a certain period of trial, when equilibrium is reached), the distance to the end (the end of the short bar with the initial profile) and the volume of the bar. To achieve this, they conducted 80 tests on flume with different wave heights and period, varying initial slopes of bed sediments and at different sizes (0.18, 0.26, 0.33 and 0.40 mm). These equations are compared with other equations proposed by other authors (Günaydın and Kabdaşlı, 2005; Hallermeier, 1978; Hsu, 1998; Larson and Kraus, 1989; Silvester and Hsu, 1997).

Demirci and Aköz (2013) by regression analysis of the data obtained in Demirci and Aköz (2012), functions such as linear and hyperbolic type are obtained, being the hyperbolic function which obtains greater regression coefficient for all parameters. These equations and results are compared with other equations proposed above. Based on the equation, Silvester and Hsu (1997) proposed more results, which is closest to the results, while the equations proposed by Günaydın and Kabdaşlı (2005) and Kömürcü et al. (2007) were those that performed least. The equations proposed by each of the authors cited above are presented in Table 1, where H_o and L_o are the height of wave and the wavelength in deep water respectively. H_b is the breaking wave height, T is the period, t test duration, d_{50} is the median sediment size, w *is* the fall velocity of the sediment and m is the slope. The breaking wave height is obtained from the formula proposed by Komar and Gaughan (1972) (Equation 2).

$$\mathrm{H_b} = \mathrm{H_o} \cdot 0.56\ (\mathrm{H_o}/\mathrm{L_o})^{-1/5} \tag{2}$$

Table 1. *Equations currently used for determining the parameters of the bars.*

On the other hand, artificial neural networks (ANNs) have been used to determine the position of the sandbars (Pape et al., 2007). However, this study only determines the distance to the shoreline, since the data were obtained from video images, so that the volume or the depth of the crest could not be determined. Neural network models are reliable to predict many aspects of cross-shore sandbar behaviour, such as rapid migration during storms offshore, onshore slower return during quiet periods, seasonal cycles and annual to inter-annual offshore-directed trends (Pape et al., 2010; Pape and Ruessink, 2011). ANN was also used by Demirci et al. (2015)to estimate the bar volume using several parameters such as bottom slope, wave period, median sediment diameter, wave steepness, showing that the presented ANN model provides better estimates for the bar volume than the other models like: multi-linear regression (MLR) models, Kömürcü et al. (2007), Larson and Kraus (1989) or Silvester and Hsu (1997). Furthermore, ANN models have been used successfully in other applications related to coastal engineering such as prediction of coastal erosion (Tsekouras et al., 2015), form plan geometry of bay beaches (Iglesias et al., 2009), coastline extraction (Rigos et al., 2016b), model seasonal changes in beach profiles (Hashemi et al., 2010), beach rotation (Rigos et al., 2016a), etc.

The aim of this study is to generate a neural network to determine the three characteristic points of the bar (start, peak and end) from empirical data collected for over 22 years of study. The results obtained are compared with the results from the equations (Table 1) proposed by various authors for each of the parameters studied.

2. STUDY AREA

The study area is located to the north and south of the port in Valencia (Spain) (Figure 1). It is a micro tidal area with astronomical tides ranging between 20 and 30 cm, which together with the meteorological tides can get up to 75 cm. It consists of fine sandy beach, with average sizes of sediments ranging from 0.172 mm to 0.452 mm (Ecolevante, 2006). The six beaches that constitute the study area cover a length of 17.7 km and two morphodynamic units. The first one, north of the port, with an approximate length of 5 km, includes the beaches of Cabanyal-Malvarrosa (P1N), La Patacona (P2N and P3N) and Port Saplaya (P4N). In the second unit, south of the port, are the beaches of Pinedo (P1S and P2S), El Saler (P3S and P4S) and La Dehesa (P5S). The nomenclature used corresponds to the code of the profiles analysed in the study area (Figure 1).

Figure 1. *Localization of the study area.*

The study area has undergone various morphological changes over the review period (22 years) due to the various regeneration and expansion of the Port in Valencia. So Pinedo Beach (P1S) was regenerated in 1999 with a volume of 215787 m^3 sand in which d_{50} existing before regeneration was 0.171 mm (Serra Peris and Medina, 1996) and 0.281 mm after (Ecolevante, 2006) regeneration. In the year 2006, the Cabanyal-Malvarrosa beach (P1N) was regenerated with a contribution of 135000 m^3 of sand, and whose d_{50} before regeneration was 0.171 mm and 0.172 mm after regeneration. This resulted in an increase in the regeneration area to 43458 m^2 (Figure 2).

The analysis of the historical evolution (comparative of historical geo-referenced orthophotos from the years 2000, 2004, 2006, 2008, 2010 and 2012 respectively) has led to the positioning of the shoreline in each of the orthophotos and then observe its tendency and the surfaces of the dry beach in each study period. Thus, it has detected a longitudinal transport to the South, so that Malbarrosa-Cabanyal beach remains the only one that is increasing its surface, thus, gaining a total of 83,628 m^2, of which just above half are as a result of the regeneration that occurred in the year 2006 (Figure 2). In the south, stands the great loss of surface (1003432 m^2) between the year 2000-2004.

Moreover, within the period analysed, the North dike of the Port of Valencia has undergone expansion (Figure 2d). Therefore, the change after this period may be due to changes in the sectors of swell of each of the beaches due to breakwater extension.

Figure 2. *Evolution of the study area. (a) Table showing the variation of the surface of the beaches. (b) Table showing incident wave in each profile before and after the expansion of the Port. (c and d) Status of the port before and after enlargement. (e) Evolution of the coastline on the south end of the beach Malbarrosa-Cabanyal.*

3. DATA COLLECTION

The procedure followed to determine the position of the bars, and to obtain the different sedimentological and wave characteristics, which will be used to define the neural network, and those required for using the proposed equations in Table 1 is described.

3.1. Bars position

In determining the position of the bars, 209 precision cross-shore profiles (error less than 2 cm) was used (Table 2). The profiles were obtained in 9 points to the North and

South of the Port in Valencia (4 to the North and 5 to the South). The profiles were taken using the method of Beach Profiler (BP) (Serra Peris and Medina, 1996). This method has a system of attachable bars with an articulated foot and a crown with two reflecting prisms that allow determining the height of the beach profile, regardless of the mean sea level by astronomical tide and wave oscillation.

Profiles survey was conducted between the 1992-1997 and 2005-2014 intervals. The frequency of intake was: i) Every 2 months between 1992-1994, ii) every 4 months from 1994 to 1997, and iii) twice a year during 2005-2014 (April and October). In this way, representative information of the summer and winter profiles are obtained in all the intervals.

Table 2. *Number of profiles and period of data collection in each of the nine points of study.*

In each of the profiles, the distance to the shoreline and the depth of the three characteristic points of the bar were obtained: i) The beginning is taken at the lowest point before the start of the bar, ii) the crest is the highest point of the bar, and iii) the end is the point where the slope changes and becomes more stretched (Figure 3). In those profiles in which no bar was found (21 profiles) the distance of each point to the coastline was obtained as the average of the position of the previous profiles, and the corresponding depth in the profile at that distance (Figure 3). Although the purpose of the neural network is to determine the characteristic points of the bar. It was decided to add the profiles data that had no bars, so that the model can provide us with more real results and confirm the presence or absence of bars.

Figure 3. *Location of the three characteristic points of the bar.*

The six data will be the neural network outputs: 1) Distance from the shoreline to the start of the bar (X_s), 2) Depth of the starting point of the bar (Y_s), 3) Distance from the shoreline to the crest (X_c), 4) Depth of the crest (Y_c), 5) Distance from the shoreline to the final point of the bar (X_f), and 6) Final point depth (Y_f).

From the analysis of each of the profiles was also obtained the difference of the beach width between them, which will be abbreviated as D_{BW}.

3.2. Maritime climate

In the study of marine climate, swell data obtained from the nodes SIMAR-2081114 (Northern zone) and SIMAR-2081113 (South zone) provided by Organismo Público Puertos del Estado were used.

In each of the profiles, the wave sectors that influenced them for each of the study periods have been sectorized and verified, so that those waves that did not affect the profile for the calculation of the waves were discarded. Then, the wave height $H_{s,12}$

(wave height exceeded only 12 hours a year, with a probability of 0.137% regardless of the studied period), maximum wave height (H_{max}), corresponding periods (T) and directions (θ) were obtained. The mean wave height (H_m) and the corresponding period (T) and direction (θ) were also calculated. Finally, the number of days elapsed between the maximum wave height and profile survey was also obtained. To calculate the above data the software Carol v1.0 (Universidad de Cantabria, 2001) was used.

Finally, the breaking wave height (H_b) was obtained using the formula proposed by Komar and Gaughan (1972) (Equation 2).

3.3. Sedimentology

Finally, using the sedimentological samples corresponding to each of the profiles, collected during the sampling campaign conducted by the University of Alicante in the year 2013, the median size of the sediment (d_{50}) were obtained according the regulation UNE-EN 933-1:2012.

4. NEURAL NETWORK

Artificial Neural Networks (ANN) is a paradigm of learning and automatic processing, inspired by the functioning of the brain. It is a system of interconnected neurons cooperating to produce a stimulus output. They appear as a field of study within the Artificial Intelligence (AI), and it was invented by shared efforts of engineers, mathematicians, physicists, computer scientists, and neuroscientists (Bishop, 1995).

The theory and modeling of neural networks is inspired by the structure and functioning of the nervous systems, where the neuron is the fundamental element. Neurons are characterized by their ability to communicate and in general terms it can be said that input signals are received that combine to emit output signals. Furthermore, each neuron receives signals through synapses that control the effects of the signal in the neuron. The main components of an ANN are: A) The synapses or connection links that provide the weights (W_i) (Figure 4) and are usually designed to minimize error in a training data set. B) One function adds the input each of values weighted $u = \sum_i W_i x_i + b$, and C) an activation function that applies $u \rightarrow y = h(u)$. In this work, the standard network that is used for function fitting is a two-layer feedforward network, with a sigmoid transfer function in the hidden layer and a linear transfer function in the output layer.

Figure 4. *Artificial neuron. w are the weights given to each input and b is the activation threshold*

The main elements of an ANN are architecture, learning algorithm and activation function and the method of determining the weights is referred to as the learning or training method. The activation functions transform the input data to output in a neuron (Fausett, 1994).

There are several kinds of ANN, such as Multilayer perceptron, Radial Basis Function nets and Kohonen's SOM. The multilayer perceptron is defined by an input layer, many hidden layers and an output layer. Neurons of the input layer are inputs to the network and the output layer produces the output of the network (Mitchell, 1997). Hidden layers receive and process information and send it to the neurons in the next layer. ANN's may recognize, classify, convert, and learn from learning samples.

The network architecture and learning algorithm are the main features of a neural network. In this study, three-layer feed-forward neural networks (A single hidden layer was used) with back propagation (BP) learning were constructed for computation of the cross-shore profile of sand beaches. A feed-forward neural network (FFNN) is very powerful in function optimization modelling and has extensively been used for the prediction of different elements related to coastal engineering (Browne et al., 2007; Herman et al., 2009; Iglesias et al., 2009; Pape et al., 2007).

4.1. Back propagation neural network and learning algorithm

The back propagation (BP) is a commonly used learning algorithm in ANN application. It uses the back propagation (BP) of the error gradient. This training algorithm is a technique that helps distribute the error in order to arrive at a best fit or minimum error. After the information has gone through the network in a forward direction and the network has predicted an output, the back propagation algorithm redistributes the error associated with this output back through the model, and weights are adjusted accordingly. Minimization of the error is achieved through several iterations. One complete cycle is known as the "epoch". Each neuron in a layer is connected to every neuron in the next layer. These links are given a synaptic weight that represents its connection strength (Govindaraju, 2000). Although, traditional BP uses a gradient descent algorithm to determine the weights in the network, it computes rather slowly due to linear convergence.

To improve speed, find the Levenberg-Marquardt (LMA), which is much faster as it adopts the method of approximate second derivative (Wang, 2004) was used here. The LMA is similar to the quasi-Newton method in which a simplified form of the Hessian matrix (second derivative) is used. The Hessian matrix (H) can be approximated as equation 3 and the gradient (g) can be computed as equation 4 (Hagan and Menhaj, 1994; Kişi and Uncuoglu, 2005).

$$H = J^T \cdot J \tag{3}$$

$$g = J^T \cdot e \tag{4}$$

in which J is the Jacobian matrix which contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. One iteration of this algorithm can be written as equation 5:

$$\chi_{k+1} = \chi_k - [J^T \cdot J + \mu I]^{-1} \cdot J^T \cdot e \tag{5}$$

where μ is the learning rate, I is the identity matrix and χ represents connection weights (Dedecker et al., 2004). During training the learning rate μ is incremented or decremented by a scale at weight updates. When μ is zero, this is just Newton's method, using the approximate Hessain matrix. When μ is large, this becomes gradient descent with a small step size (Karul et al., 2000).

Bayesian regularization (BR) is a training algorithm that updates the weights and bias values according to LMA optimization (Foresee and Hagan, 1997; MacKay, 1992). It minimizes a combination of squared errors and weights, and then determines the correct combination so as to produce a network that generalizes well (Pan et al., 2013). BR introduces network weights into the training objective function which is denoted as $F(\omega)$ in equation 6 and further explained by Yue et al. (2011).

$$F(\omega) = \alpha E_\omega + \beta E_D \tag{6}$$

Where E_ω is the sum of the squared network weights and E_D is the sum of network errors. Both α and β are the objective function parameters. In the BR framework, the weights of the network are viewed as random variables, and then the distribution of the network weights and training set are considered as Gaussian distribution.

The α and β factors are defined using the Bayes' theorem. The Bayes' theorem relates two variables (or events), A and B, based on their prior (or marginal) probabilities and posterior (or conditional) probabilities (Li and Shi, 2012). After finding the optimum values for α and β for a given weight space, the algorithm moves into LMA phase where Hessian matrix calculations take place and updates the weight space in order to minimize the objective function. Then, if the convergence is not met, algorithm estimates new values for α and β and the whole procedure repeats itself until convergence is reached Yue et al. (2011).

MATLAB (MathWorks, Inc., Natwick, MA) was used for analyzing the BR Artificial Neural Network (BR) and LM Artificial Neural Network (LMA). To prevent overtraining, develop predictive ability, and eliminate superiors' effects caused by the initial values, the algorithms of BR and LMA were trained independently 50 times for each generated model. In this study, the training process is stopped if: 1) it reaches the maximum number of iterations; 2) the performance has an acceptable level; 3) the estimation error is below the target; or 4) the LMA μ parameter becomes larger than 10^{10}.

4.2. Optimization of the ANN structure and modelling performance criteria

When selecting the optimal architecture of a network, it must be designed according to the physical problem posed. The models and the input and output vectors, along with the network parameters are fundamental steps for designing the ANN. Therefore, the input layer will be formed by the physical factors that affect the development of the bars, with 7 input neurons corresponding to the following variables: 1) Month of survey profile (x_1); 2) Steepness corresponding to the maximum wave height (x_2); 3) H_{max} direction (x_3); 4) Days elapsed from H_{max} to the survey profile (x_4); 5) H_m (x_5); 6) d_{50} (x_6); 7) Difference in beach width between profiles (x_7). Some of these factors (wave height, the depth, direction or grain size) have been used by other authors (Günaydın and Kabdaşlı, 2005; Horikawa et al., 1973; Kömürcü et al., 2007). However, it was felt necessary to use other variables that reflect changes in the study area as the change in the width of the beach. Finally, use the Month of the profile survey has been considered to mark the change of season that occurs in the area, as the wave heights in the area did not suffer a great variation between summer and winter. The output layer is formed by six neurons corresponding to the distance and depth of the three studied points (X_s, Y_s, X_c, Y_c, X_f and Y_f).

The used network is a multilayer perceptron in which a total of 209 data have been used. Executions were carried out by changing the percentages of training, validation and test. From the study of these executions it was observed that the most consistent and most satisfactory results corresponded to 85% (177) of training and validation and 15% (32) of test. The model is also trained by Bayesian Regularization and Levenberg-Marquard algorithms, thus, obtaining better results with the first method. To select the optimum number of neurons, 20 different architectures were tested, increasing neurons in the hidden layer one at time from 1 to 20. For each architecture, 50 executions were carried out in which data for training and testing were chosen at random by the program MATLAB (MathWorks, 2005). Since the choice of data for training and testing is random, we can not determine which profiles have been used in each group, so the error calculation is performed for each and every one of the 209 profiles.

In order to choose the best model, the Pearson coefficient (R^2) was used as information parameter in training, in test and together. The absolute error (Equation 7), the average magnitude of relative error (MAPE) (Equation 8) and the relative percentage error (Equation 9) is also used to determine the best model.

$$e = |r_i - o_i| \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{r_i - o_i}{r_i}\right| \tag{8}$$

$$\delta = \sqrt{\frac{\sum_{i=1}^{n}(r_i - o_i)^2}{(n-p)\frac{1}{n}\sum_{i=1}^{n}(r_i)^2}} \tag{9}$$

Where r_i corresponds to the measured values, o_i with the values obtained from the network, n is the number of values and p is the number of free parameters of expression.

Of the set of 20 architectures, the best results are those of 12 and 20 neurons in the hidden layer. Figure 5 shows the average, maximum and minimum of R^2 in the test for each of the architectures. The [7-12-6] architecture was finally chosen as the average value of R^2 is one of the largest, and the difference between the maximum and minimum values is the smallest, which means that this architecture offers the most stable results, and also has a smaller number of neurons in the hidden layer. In Figure 6, the selected architecture is shown.

Figure 5. *Mean, maximum and minimum values of R^2 for the whole test.*

Figure 6. *Optimal architecture [7-12-6].*

Figures 7 and 8 show the absolute error and the average for each of the six outputs of the chosen network architecture of [7-12-6]. The mean error for distances to shore (Figure 7) is between 13.6 and 23.9 m (13.6 m in X_s, 14.5 m in X_c and 23.9 m in X_f), which is an error of 14.2% in X_s (mean distance of 96 m), 11.5% in X_c (average of 126 m) and 11.9% in X_f (average of 197 m). While the error in the depths (Figure 8) are 0.28 m, 0.25 m and 0.26 m at the start, the crest and the final point respectively, thus committing an error of 10.7% in Y_s (mean depth of -2.62 m), 10.1% in Y_c (mean of -2.47 m) and 6.9% in Y_f (mean of -3.59 m). The largest errors often occur almost always in the same profiles, such as 11, 156, 180, 184 and 194.

Figure 7. *Absolute error (m) committed for distances to shore in each of the network outputs.*

Figure 8. *Absolute error (m) committed for depths in each of the network outputs.*

The mean MAPE of the ANN is 0.3 (Figure 9), being 80% of profiles below this value, in this case the profiles 56, 120, 180 and 199 produce the greatest error. In these profiles, the same as the profile 180 occurs, the bars are very close to the coastline, being located 42 m in the middle. Figure 9 also shows the relative percentage error of the network for which the value is less than 5.1% in all cases with an average of 1.7%.

Figure 9. MAPE and δ at each studied profile.

5. DISCUSSION

In this study, different architectures of ANNs required to locate the three characteristic points of a bar have been generated. An architecture of the type [7-12-6] has been selected, being offered the highest values of the coefficient of Pearson in the training, test, and together, as well as lower absolute errors.

It is observed that the mean absolute error (Figures 7 and 8) is 13.6 m in X_s, 14.5 m in X_c, 13.9 m in X_f, 0.28 m in Y_s, 0.25 m in Y_c and 0.26 m in Y_f, being the error around, 12.5% in the distances to the coast and 9.2% in the depths. The profiles that produce the biggest mistakes are 11, 156, 180, 184 and 194. The MAPE (Figure 9) in turn, has an average of 30%, with much more higher value in the profiles 56, 120, 180 and 199. The relative percentage error generally have small values with an average of 1.7% (Figure 9).

From the analysis of the profiles, it is observed that the biggest errors occur in those in which there were no bars (11, 156, 184 and 194) (Figure 10). In these profiles, the neural network tends to generate a small bar, because the number of profiles without bar is very low compared to the total (21/209). Furthermore, the problem of the profiles 56, 120, 180 and 199, is that the bars are located much closer to the coast (crest is an average of 42 m) than the other profiles in which the crest is generally around 126 m (Figure 10).

Figure 10. *Comparison between real points of the bar and points obtained by the ANN.*

Finally, the error made using the ANN model has been compared with some of the functions currently used, as displayed in Table 1. Figure 11 shows the comparison between R^2 and MAPE for each of the outputs of the network and the functions proposed by each of the authors. It is observed that the error made by using any of the proposed equations is greater than committed by the ANN in all cases. As an example, the MAPE committed by the proposed equation for distance to shoreline of the crest is 47%, while the ANN is 29%. This error difference is mainly because the formulas have been developed from tests on flume, and therefore do not take into account the complexities of a natural beach as morphological changes and/or irregular wave. However, these effects are very important and cannot be neglected in an area such as the study area, which suffered serious erosion problems and has suffered various nourishments in the last years (Figure 2). Moreover, taking into account the changes the area has undergone both natural and artificial (port expansion, nourishments, etc.), the mistakes made by the neural network are admissible because they are only 17.3 m in the distance waterfront and 0.26 m in depth in comparison with the current formulas (Figure 11).

Figure 11. *Comparison of R^2 and MAPE of the equations used today and ANN. The X-axis shows a comparison between each of the authors using initials; H: Horikawa [1973], Haller.: Hallermeir (1978), L&K: Larson and Kraus (1989), S&H: Silvester and Hsu (1997), Hsu: Hsu (1998), G&K: Günaydın and Kabdaşlı (2005), K: Kömürcü et al. (2007), and D&A: Demirci and Aköz (2013).*

The correct determination of the location of the sand bars has important implications in coastal engineering. Therefore, if we are able to determine the exact position or range of motion of the rods we can determine more accurately the elements influencing the calculation of the elements of protection of the coast or the volumes of sand required for a beach nourishment. For example, when calculating the position of a detached breakwater have to calculate the depth of closure, which must be located offshore the end point of the bar. In this case, for example, the difference between using the results obtained with the ANN or the current proposed equations would mean a difference of 0.7-2.5 m depth which is a big difference in the volume of material needed for the construction of the element of protection.

On the other hand, the use of the ANN can offer simulated data to the future, which will allow to know what the movement of the bar would be in front of future storms, from which it could be determined the influence that a storm could have in the width and the erosion of the beach, and the subsequent recovery in the calm period. Thus, this tool associated with other similar tools such as erosion determination (Tsekouras et al., 2015) or bar volume (Demirci et al., 2015), becomes not only a tool for the knowledge of the bars, but is an additional element for coastal management and control, which may imply a reduction in both construction and maintenance costs.

6. CONCLUSION

ANN model is used for predicting the three characteristic points of the bar (start, crest and final point) depending on wave action, sediment and the date of the profile survey. These characteristics are represented by the following inputs: *Month*, H_{max}/L_o, ϑ_{Hmax}, *Days*, H_m, d_{50} and D_{BW}. The analysed beaches are complex beaches that have undergone various morphological changes within the study period (22 years) due to the expansion of the Port in Valencia and the beaches nourishment. The outputs were obtained from precision profiles taken for 22 years, particularly in the months of April and October. 20 architectures are designed for each, thus, obtaining 50 different models. For the selection of the optimal architecture, Pearson coefficient (R^2) has been used as an informative parameter in the test, training and together, being the best model that uses 12 neurons in the hidden layer [7-12-6]. To evaluate the performance of the model, we used the absolute error (Equation 7), the average magnitude of relative error (Equation 8) and relative percentage error (Equation 9). The mean absolute error is 17.3 m for distances to the coast and 0.26 m in depth. Physical analysis shows that the largest errors occur in those profiles in which there was no bar, as these represent only 10% of the data, and the profiles in which the bar is located much closer to the coast than the average value. Even so, the error committed by the ANN is much less than the commited by using the current formulations (Table 1 and Figure 11), which is mainly due to the fact that these formulations are usually obtained from experiments in flume, and therefore, do not take into account the variability of the actual waves or morphological complexities that can affect the study area.

Therefore, the results of this work could be used in other areas as an effective tool in predicting the position of the bars.

ACKNOWLEDGEMENTS

The authors want to thanks the Jefatura Provincial de Costas de Alicante and Organismo Público Puertos del Estado (www.puertos.es) for the information provided has enabled this study. And the University of Alicante for lending facilities.

This research has been partially funded by Universidad de Alicante through the project “Estudio sobre el perfil de equilibrio y la profundidad de cierre en playas de arena” (YGRE15-02).

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