Correlating Wave Hindcast and Buoy data with Artificial Neural Networks

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ABSTRACT:
This work presents results from the use of Artificial Neural Networks (ANN) to improve wave models hindcasting capacity off the South coast of Portugal. Comparison of the original model results with field measurements showed significant non linear deviations. To compensate for such deviations, a three-layer Multilayer Perceptron (MLP – a type of an ANN) was trained, using the Levenberg-Marquardt method, to improve the fit between the hindcast (generated by WW3) and Faro buoy data in an effort to reconstruct missing data from the wave buoy time series. The results obtained so far are very positive; with the training with annual datasets showing better results than the training with the entire dataset, while both improved significantly the fitting of the raw model results. Further improvements are expected by trying different ANN types, by searching for optimised ANN input-output structure, and by performing sub-set selection on the data sets.

KEYWORDS: Artificial Neural Networks, Hindcast wave model, wave data.

1. INTRODUCTION

In-situ deployed instruments, such as buoys, are invaluable sources for continuous long-term oceanographic data acquisition, which is fundamental for a variety of research and operational applications. Given the rough and unfavourable conditions in the ocean, data gaps are a common consequence of instrument loss, malfunctioning, or delayed maintenance and data collection, being a major problem for data analysis. As an example Figure 1 characterize the data gaps (more than 3h without data) present on a wave time series obtained from the Faro Directional Wave Buoy (Portuguese Hydrographical Institute - IH), between 2000 and 2006.

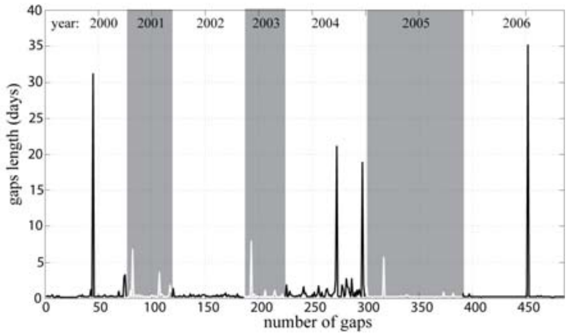

Figure 1. Number and length of gaps present in a wave time series obtained from Faro Wave buoy (IH).

Periods without data can last from three hours to several days or weeks and simple interpolation methods are usually not an acceptable approach. One solution for these cases is to fill the gaps with results obtained by a wave generation model, e.g. WAVEWATCH III™ (Tolman, 2009). However wave models are highly-dependent on the quality and resolution of the wind forcing (Cavaleri and Bertotti, 2006; Ponde de Léon and Guedes Soares, 2008) and model results often show significant deviations from the real data at sheltered locations where local winds play an important role on the wave climate (Figure 2).

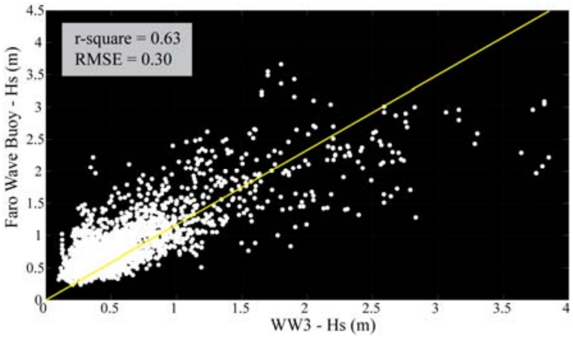

Figure 2. Linear correlation between Hs Faro buoy and WW3, for the year 2004.

One way to solve this non linear problem is through the use of artificial neural networks (ANN), since these are a modelling tool that can be used to model complex relationships between inputs and outputs.
There are already in the bibliography some examples of the applications of ANN's in ocean engineering like to reconstruct wave time series using information from neighbourhoods buoys (Deo and Kumar, 2000; Puca *et al.*, 2001; Londhe and Panchang, 2007;Medina and Serrano-Hidalgo, 2004) or for wave forecasting (Tsai et all., 2002; Makarynskyy , 2004; Makarynskyy *et al.*, 2005;) using historical data from buoy for training.

The aim of this work is to train a three-layer Multilayer Perceptron (MLP – type of an ANN) to improve the fit between the hindcast (generated by WW3) and Faro buoy data in order to reconstruct missing data from the wave buoy time series.

2. METHODS

2.1 ANN Description

A neuron is defined as an information-processing unit that is fundamental to the operation of a neural network. Figure 3 shows a simple one-neuron model to illustrate the neural networks structure.

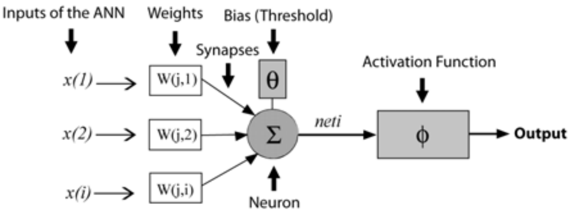

Figure 3. Model of a typical neuron.

The neuron includes a set of *synapses* or *connecting links*, each link connecting the respective input to the summation block. Associated with each synapse, there is a *strength* or *weight*, which multiplies the associated input signal. The input signals are integrated in the neuron. Usually an *adder* is employed for computing a weighted summation of the input signals. The resulting sum is adjusted by a bias to become the net input of the activation function, which limits the output of a neuron to some finite value (Bose and Liang, 1996). The mathematical expression for a neuron (j) can be written as:

$$net_j = \sum_{i=1}^{n} \left(w_{ji} x_i \right) + \theta_j \qquad (1)$$

$$y_i = \phi\left(net_j \right) \qquad (2)$$

Where net_j is the input of the neuron j, x_i the ith input of the neuron, w_{ji} the weight for the input i and neuron j, θ_j the bias, ϕ the activation function, and y_i the output of the neuron j.The activation function is used to transform the activation level of a unit (neuron) into an output signal. The ANN process consists of two stages: learning and recalling. In the learning stage, the algorithm continuously adjusts the weights of the neurons. Once proper weights are found, they are fixed in the recalling stage that the model can be further tested with other samples.

Training can be considered as a general function optimization problem, with the adjustable parameters being the weights and the biases of the network, and one of the most accepted methods to solve this problem is the Levenberg-Marquardt. A review on the Levenberg-Marquardt method can be found in Suratgar *et al.* (2005). The general scope of the learning optimization is to reduce the error between the desired output (target) and the actual output. The error E, is defined as the sum-squared differences between the values of the outputs of the network and the desired target values:

$$E = \frac{1}{2} \sum_j \left(d_j - y_j \right)^2 \qquad (3)$$

Where d_j and y_j are the desired and actual output values of the output neuron j.

2.2 Multilayer Perceptron

One of the most common methods used in ANN is the Multilayer Perceptron (MLP). With MLP is possible to have more than one layer of neurons inside the network, known as hidden layers, which can improve the network computation (Figure 4). With this network structure the outputs of each neuron represent the inputs of the next above neuron.

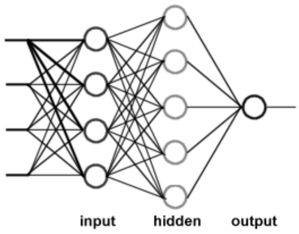

Figure 4. Model of a Multilayer Perceptron with 1 hidden layer.

2.3 Wave data acquisition

The significant wave height (Hs) from two distinct sources was considered for the present analysis: (i) wave measurements obtained from a directional wave buoy (Figure 5) operated by the Portuguese Hydrographical Institute and located off S^{ta}. Maria Cape (Faro) - the data set extends from 2000 to 2006, presents gaps (Figure 1) and a frequency acquisition of 3 hours; (ii) continuous modeled wave data at the nearest location to the wave buoy (Figure 5) with a time-step of 3 hours;.these outputs are derived from a one-way nesting application of the WaveWatch III (WW3) regional model described in Dodet et al. (2010).

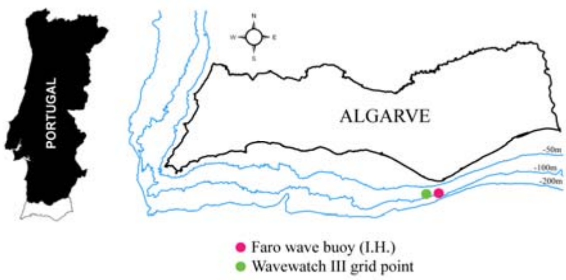

Figure 5. Location of the wave data sources.

2.4 Network inputs and targets

For this work only the parameter H_s was tested as target. Nevertheless, the same structure of implementation can be applied for other wave variables (e.g. wave period and direction). Two types of tests were preformed for the present work: 1) using the entire dataset (covering the whole 6 year span) testing two different topologies (*test 1* and *2*); *2)* training each year of data separately, testing in all the cases the same topology (*test 3, 4, 5, 6, 7, 8, 9*); The architecture of each test is present in Table I. For each network 70% of the data was used for training and 30% for validation.

Table I. ANN architectures for each test.

Test	Topology (input-hidden-output)	Record number	year
1	[9 30 1]	18382	2000-2006
2	[9 50 1]		
3	[9 30 1]	2521	2000
4		2786	2001
5		2833	2002
6		2817	2003
7		2283	2004
8		2771	2005
9		2371	2006

Each of the tests presented was implemented using the same input structure:

[***Hs***(*t*-2*Δt*) ***T***(*t*-2*Δt*) ***Dir***(*t*-2*Δt*) ***Hs***(*t*-*Δt*) ***T***(*t*-*Δt*) ***Dir***(*t*-*Δt*) ***Hs***(*t*) ***T***(*t*) ***Dir***(*t*)]

Where *Hs* is the significant wave height, *T* the wave period, *Dir* is the wave direction, *t* is the time instant with Δt = 3 hours. For the targets the structure present in every simulation was [***Hs***(*t*)].

3. RESULTS

The performance of the training tests was evaluated by comparing the coefficient of determination (r^2) and the root mean squared error (RMSE) between the target (IH) and the output data (trained WW3) against the r^2 and RMSE between the same target (IH) and the non trained WW3 data (Figure 6).

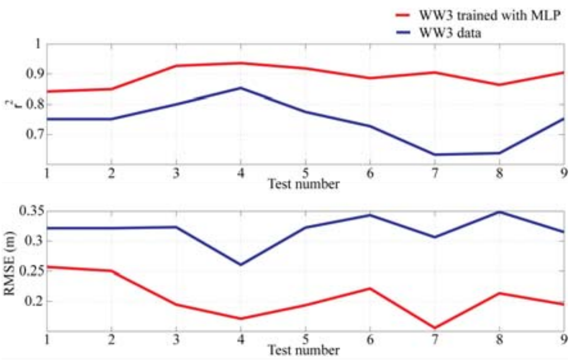

Figure 6. Performance of the training tests and non trained WW3 data against the IH buoy data.

Comparisons show that modelled data trained with ANN's has improved significantly the correlation between the wave buoy and WW3 data (presenting r^2 always above 0.8) and reduced the RMSE (with values always bellow 0.25 m).

The implementation of ANN's using annual data instead of the complete series (*tests* 3 to 9) further improved the fitting (Figure 7).

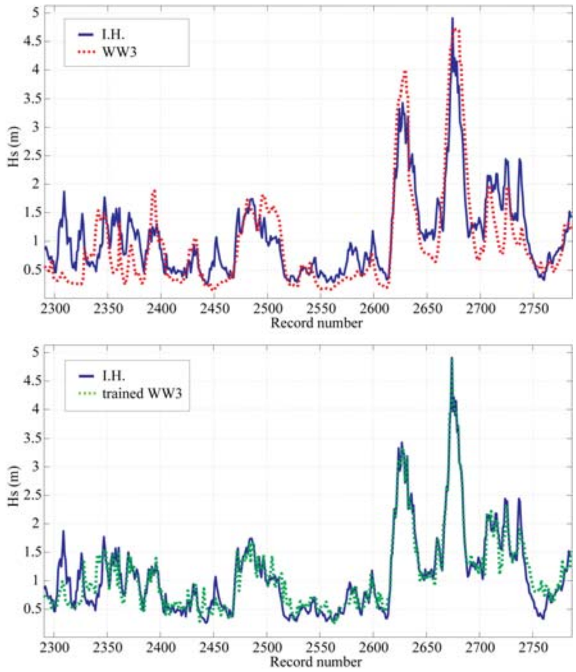

Figure 7. Example of the results obtained for *test* 4.

4. FINAL CONSIDERATIONS

The present contribution presents promising preliminary results from the use of ANN's to improve wave hindcast model results. Comparisons between non-trained and trained outputs show a significant improve on data quality when compared with buoy observations. The training with annual datasets show better results than the training with the entire dataset, while both improved significantly the fitting of the raw model results. The work is currently on progress and further improvements are expected to find the best architecture of ANN and dataset structure.

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