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A Method for the Separation of Wind Generated and Traveling Waves in Coastal Zones and its Use in Wave Height Prediction

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The most widely used and accepted method of studying wind generated waves is an examination of the spectra at a single point. This approach is based mostly on the assumption that recorded time series of the surface elevation, pressure or velocities are the results of linear superposition of small amplitude oscillations regardless of their directions of propagation. In this work, the vertical and horizontal accelerations of a floating buoy have been used in order to calculate the directional wave spectra in coastal zones. The method used is a parametric one, which incorporates two waves propagating in different directions. The resulting splitting of the incoming waves into two main directions is used for 24-hours wave height prediction with an adaptive neural network.

1 Introduction

The most widely used and accepted method of studying wind generated waves is an examination of the spectra at a single point. This approach is based mostly on the assumption that recorded time series of the surface elevation, pressure or velocities are the linear superposition of small oscillations regardless of their directions of propagation [1]. Due to complicated energy transfers from the atmosphere to the sea, the resulting surface waves are multidirectional, with only some of the waves aligned with the wind direction. Wave multi-directionality is also a result of the superposition at a given point of a number of wave trains which may be generated by different and remote atmospheric forcing systems.

The spreading of wave energy in many directions is a fundamental property of a random wave field. Information about the directional distribution of wave energy is required for the proper prediction of various oceanographical and geomorphological phenomena in shallow and deep waters.

Analysis of raw data is based on the so called 'stochastic model' [2]. In this approach, the sea surface elevation is considered to be a Gaussian random variable (linear model). The first few terms of the Fourier transform of the spectrum of this random variable can be calculated, given that certain moments of the spectrum are known (from measurements). Since in the majority of experiments, we are dealing with single point measurements, the small number of Fourier coefficients that can be calculated leads to a poor estimation of wave field directionality.

The calculation of certain moments of the wave spectrum from real-time measurements can be used directly for short term wave height prediction. A popular method which can handle efficiently non linearities is that of neural networks [3]. Wave height time series can be used to train either an adaptive or a static neural network, leading thus to a system capable for predicting the evolution of the wave height for the next few hours. The performance of such systems can be further increased by including estimates for the evolution of the wind (speed and direction). There are however cases that although the present conditions are similar, the resulting wave height differs due to traveling waves (swell). In order to overcome this problem, information about the nature of the present wave field are necessary.

In this paper, a parametric method is presented for calculating the directional wave spectrum from vertical and horizontal accelerations of a floating buoy. These measurements are simple and the sensors used are of low cost. The method assumes the superposition of two independent wave trains giving a better approach to the multidirectional nature of the wave field. The produced method is applied to data obtained from the POSEIDON

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system [4] in the Greek seas. The resulting splitting of the incoming waves into two main directions is used for 24-hours wave height prediction with an adaptive neural network.

2 Formulation of the problem

The following analysis for the determination of the directional wave spectra can be applied when the wave sensors give the vertical and horizontal accelerations of the floating buoy. In these cases, the accelerations can be twice integrated and thus can be transformed in vertical and horizontal shifts. According to Linear Wave Theory [5], the directional wave spectra $E(\omega, \theta)$ is given

$$E(\omega, \theta) = S(\omega) \cdot D(\omega, \theta) \tag{1}$$

where $S(\omega)$ is the total wave power at frequency ω and $D(\omega, \theta)$ is the distribution of this power over all possible directions. Notice here that the integral of $D(\omega, \theta)$ over all possible directions is normalized to unity. It is reasonable to assume here that the main direction of wave propagation is that of the generating wind (since we are talking for waves in coastal zones). But the experiment shows that this is not true. The wave power is distributed in all directions located near a dominating one. A parametric model for this distribution is given [6],[7]

$$D(\omega, \theta) = \hat{D}(\omega) \cdot cos^{2p(\omega)} \left(\frac{\theta - \theta_0}{2} \right) \tag{2}$$

where θ_0 is the main direction and $p(\omega)$ is an integer which depends on frequency. This model describes well the local wind generating waves but fails when the wave field contains propagating waves from other directions like swells.

In order to account for this problem, we assume that the wave field is is composed by a local wind generated one (located at direction θ_0) and a propagating field (located at direction θ_1). Thus, the directional spectrum can be expressed [8]:

$$D(\omega, \theta) = \Delta_0(\omega) \cdot cos^{2p(\omega)} \left(\frac{\theta - \theta_o}{2} \right) + \Delta_1(\omega) \cdot cos^{2p(\omega)} \left(\frac{\theta - \theta_1}{2} \right) \tag{3}$$

The exponent $p(\omega)$ is considered to be an integer and the same for the two components of the wave field. This is necessary, since otherwise it will result an indefinite system of equations.

Using the above expression for the directional component of the wave field, we can calculate the different cross spectra as follows:

$$C_{nn} = I(p)(\Delta_0 + \Delta_1) \tag{4}$$

$$C_{xx} = \frac{k^2 g^2}{\omega^4} \cdot I(p) \cdot \left[\Delta_0 \left(\frac{1}{2} + \frac{p(p-1)cos2\theta_0}{2(p+1)(p+2)} \right) + \Delta_1 \left(\frac{1}{2} + \frac{p(p-1)cos2\theta_1}{2(p+1)(p+2)} \right) \right] \tag{5}$$

$$C_{yy} = \frac{k^2 g^2}{\omega^4} \cdot I(p) \cdot \left[\Delta_0 \left(\frac{1}{2} - \frac{p(p-1)cos2\theta_0}{2(p+1)(p+2)} \right) + \Delta_1 \left(\frac{1}{2} - \frac{p(p-1)cos2\theta_1}{2(p+1)(p+2)} \right) \right] \tag{6}$$

$$C_{xy} = \frac{k^2 g^2}{\omega^4} \cdot I(p) \cdot \left(\Delta_0 \frac{p(p-1)sin2\theta_0}{2(p+1)(p+2)} + \Delta_1 \frac{p(p-1)sin2\theta_1}{2(p+1)(p+2)} \right) \tag{7}$$

$$C_{nx} = \frac{kg}{\omega^2} \cdot I(p) \cdot \left(\Delta_0 \frac{p \cdot cos\theta_0}{p+1} + \Delta_1 \frac{p \cdot cos\theta_1}{p+1} \right) \tag{8}$$

$$C_{ny} = \frac{kg}{\omega^2} \cdot I(p) \cdot \left(\Delta_0 \frac{p \cdot sin\theta_0}{p+1} + \Delta_1 \frac{p \cdot sin\theta_1}{p+1} \right) \tag{9}$$

where n stands for the vertical and x, y for the horizontal components. The function $I(p)$ is given

$$I(p) = 2\pi \frac{1 \cdot 3 \cdot 5 ... (2p-1)}{2 \cdot 4 \cdot 6 ... 2p} \cdot \frac{p}{p+1} \tag{10}$$

3 Numerical results

Figure 1 shows the wave spectrum for two different events. In the first one, there was an almost constant in direction wind field during the previous few days. Thus, a unidirectional wave field has been developed. In figure 1(a), the wave spectra is shown as calculated with the classical Lonquet-Higgins method [5]. Since in this method, only the first terms in the Fourier expansion of the wave field are calculated, effects like broadening or aliases are very common. Figure 1(b) shows the wave spectrum as calculated with the new method. Aliases are eliminated and the spectrum is narrower as far as the angular distribution is concerned. The second case is more interesting and concerns an event in which wind changed its direction in a counter clockwise direction starting from the North and finally ending in West-East. Figure 1(c) shows the wave spectrum as calculated with the classical Longuet-Higgins method [5]. The method only produces an average spectrum, resulting in a false estimation of the wave direction. Figure 1(d) shows the wave spectrum for the same event as calculated with the new method. The two waves are now clearly separated. The main wave is coming from the West-East while a remaining (traveling swell) wave is coming from the North. The information about these two waves can be valuable in wave prediction.

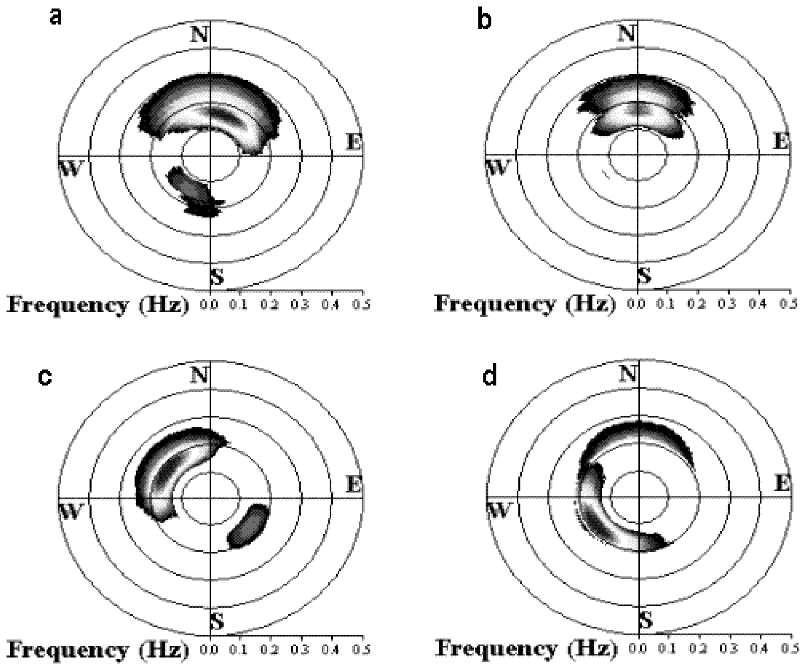

Fig. 1 Wave spectrum as calculated with the classical Longuet-Higgins (a,c) and the new method (b,d).

In order to test the new method and its usage in wave prediction, an experiment was performed. An adaptive neural network was used to predict the wave height for the next 24 hours. The architecture and dynamics of the neural network are described elsewhere [3]. Two configurations of the neural network were simultaneously running. In the first one, the input of the network was the wave height time series as calculated with the classical Longuet-Higgins method [5] and the wind time series. In the second configuration, in the input of the neural network, the wave height was represented with the two wave components calculated with the new method. The first component corresponds to the wind generated wave while the second to swell. The problem that we are trying to solve here is the following. By feeding the neural network with patterns from wave height and wind time series it is expected that after a reasonable training period, the network will be able to predict the wave height in the next time step. In order to obtain this, it is necessary that the learning sets (inputs and corresponding desired outputs) are stable and not conflicting. Consider now the case that is depicted in figure 1(a) and 1(b). Since the wave here is unidirectional and has the same direction as the wind, the network is expected to learn easily these patterns. On the other hand, in case like the one depicted in figure 1(c) and 1(d), the false estimation of the wave direction in collaboration with the wind input pattern result in a twofold effect: the network finds very difficult to follow these patterns while it is possible to alter its response to already learned patterns.

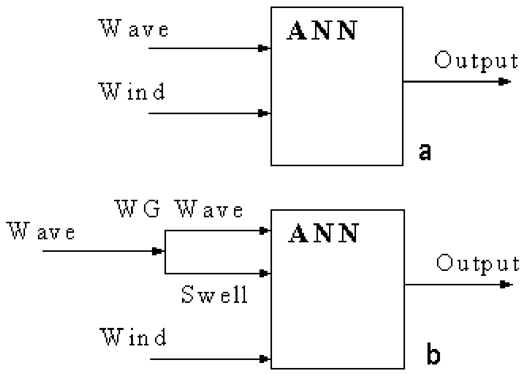

Fig. 2 Two configurations for wave height prediction. (a) The input of the Adaptive Neural Network is the wave height series calculated from the first Fourier coefficients. (b) The input of the same network is the wind generated wave and the swell as calculated from the proposed method.

Figure 3 shows the results of the prescribed experiment. Solid line represents the actual wave height, squares represent the prediction from the numerical model running on the POSEIDON system [4], rhombus represent the prediction produced from the neural network when the input wave pattern is calculated with the classical Longuet-Higgins method [5] and circles represent the prediction from the neural network when the input wave pattern is calculated with the new method. The numerical model cannot follow the actual values of the wave height due to failures of the wind prediction numerical model in which the wave model is based. The use of neural network can overcome this difficulty because it takes into account the wave height time series. The decomposition of the wave in wind generating and traveling one can dramatically increase the efficiency of the predicting system.

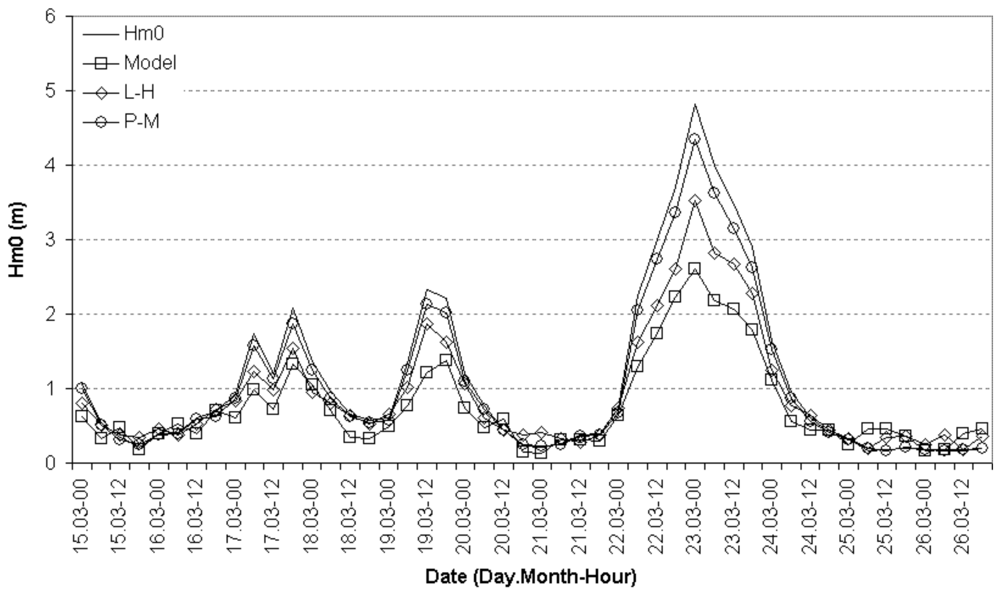

Fig. 3 Actual wave height (solid line) and predicted wave height with the POSEIDON numerical model (squares), the neural network with wave height input calculated with the classical method (rhombus) and the neural network with wave height input calculated with the new method (circles).

4 Conclusions

The use of a parametric method for the calculation of the wave spectra is presented. The method assumes that the actual waves are the superposition of a wind generated and a traveling (swell) wave. This decomposition of the wave field overcomes several shortcomings of the classical method of wave spectrum calculation, like broadenings and aliases. Moreover, the extra information of the constituents of the wave fields can increase the efficiency of wave height predicting systems.

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