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Modelling of the sea surface elevation based on a data analysis in the Greek seas

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ABSTRACT

The theory of time series and especially of the autoregressive moving average (ARMA) models is used for modelling the sea surface elevation. Sea surface elevation is usually recorded by wave measuring devices, but rarely has it been analysed or analytically modelled. Except other traditional applications, forecasting of the wave characteristics in the short-term time scale is important for the optimization of the efficiency of the wave energy converters. The main objective of this work is, by using the Box-Jenkins methodology, the analytical description and forecasting of the sea-surface elevation process. A sample of 50825 records of sea surface elevation was collected by four different deep water locations at the Aegean and Ionian seas in Greece from 2000 to 2011. Analytical ARMA(p,q) models were fitted to a variety of potential parameter combinations, i.e. p, q = {0,1,2,3,4,5} for the examined time series in order to identify the most suitable ARMA model for this purpose. The diagnostic and suitability check, as well as the selection of the best model is carried out according to the Akaike and the Bayesian information criteria. The results obtained suggest that the ARMA(2,5) model is the optimum choice for the representation of the sea surface elevation. A further attempt has been made in order to highlight a possible relation between the best ARMA models and various spectral characteristics such as the significant height, the spectral peak period, the mean wave direction and the spectral bandwidth parameters of the corresponding sea-state. Finally, based on the best-fit ARMA model, a forecast of free surface elevation is carried out, confirming the model sufficiency by estimating the forecast errors.

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1. Introduction

The assessment and modelling of prevailing wave conditions in a sea area is of interest for ship design, harbour activities, and operational service of platforms. Wave energy applications and the optimal efficiency of the wave energy converters are also directly related to the forecasting of sea surface elevation (sse). Wave climate and sea state parameters such as the significant wave height, the spectral peak period and the mean wave direction are of great importance in marine structural design and ocean engineering. Therefore, several studies have analysed and modelled time series of relevant wave parameters at different locations. The majority of them focuses on wave spectral characteristics and in particular on the significant wave height. However, time series of sse has rarely been analysed.

The sea surface elevation, denoted as $\eta(t)$, at a fixed position of the free surface, is represented as a stationary, ergodic and Gaussian stochastic process of the following form:

$$\eta(t;\beta) = \sum_{i=1}^{\infty} A_i cos[2\pi f_i t + \varphi_i(\beta)], \tag{1}$$

where A_i is, at each frequency, Rayleigh distributed and denotes the amplitude, $\varphi_i\left(\beta\right)$ is the phase, which is modelled as a random variable uniformly distributed in $[0, 2\pi]$, f_i is the frequency of small amplitude components of (1), i.e. $f_i = 1/T_i$, where T_i is wave period, and $i = 1, 2, \ldots$; β is a choice variable. See also [1] and [2].

Each particular record $\eta(t)$ of the free sse is considered as one of the infinite possible realizations that could occur in the same place and under the same experimental conditions. Since the stochastic process which is represented by relation (1) is ergodic, the statistical analysis of the stochastic process is practically feasible from only one realization of it. A realization of $\eta(t;\beta)$ is a set of records $\eta(t)$ at every time instant t. In practice, this realization consists a discrete-time time series, i.e. $\eta(t_i) = \eta(t_1), \eta(t_2), \ldots, \eta(t_n)$.

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According to Chatfield [3], Hamilton [4] and Wei [5], time-series analysis involves the evaluation of the properties of the underlying probability model from the observed time series. In the statistical analysis of time series there exist analytic models that provide a parsimonious description of a stationary stochastic process in terms of polynomials. The most fundamental of these models are the moving average (MA) and the autoregressive (AR) model.

Let X_t, $t = 1, 2, \ldots$ denote a time series; then, an autoregressive model AR(p) of order p, is of the form

$$X_t = c + \alpha_1 X_t - 1 + \alpha_2 X_t - 2 + \ldots + \alpha_p X_{t-p} + \varepsilon_t, \tag{2}$$

where c is a constant, $\alpha_1, \alpha_2, \ldots, \alpha_p$, are parameters to be estimated and ε_t is a zero-mean white noise process. From Eq. (2) it is evident that the current value of the variable X_t is a linear combination of past values $X_t - 1, X_t - 2, \ldots, X_{t-p}$ of the same variable. Using the backshift operator B, relation (2) can be written as follows:

$$X_t = c + \sum_{i=1}^{p} \alpha_i B^i X_t + \varepsilon_t. \tag{3}$$

In order the model (2) to be stationary in the wide-sense, each root z_i of the polynomial $z^p - \sum_{i=1}^{p} \alpha_i z^{p-i}$ should satisfy the condition $|z_i| < 1$.

The moving average model MA(q) of order q is defined as follows:

$$X_t = \mu + \varepsilon_t + \beta_1 \varepsilon_t - 1 + \beta_2 \varepsilon_t - 2 + \ldots + \beta_q \varepsilon_t - q, \tag{4}$$

where μ is the mean value of the time series, $\beta_1, \beta_2, \ldots, \beta_q$ are parameters and ε_t are white noise process error terms; see also Shumway and Stoffer [6]. In this case, the current value of the variable X_t is a linear combination of past values forecast errors ε_{t-1}, $\varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$.

A mixed form that combines AR(p) and MA(q) refers to a model with p autoregressive terms and q moving-average terms. This model is usually in practice, more useful and efficient. The mixed autoregressive moving average (ARMA) model of order (p, q), known as ARMA(p,q) model, contains both AR and MA terms and is given by the following relation:

$$X_t = c + \alpha_1 X_t - 1 + \alpha_2 X_t - 2 + \ldots + \alpha_p X_{t-p} + \varepsilon_t + \beta_1 \varepsilon_t - 1 + \beta_2 \varepsilon_t - 2 + \ldots + \beta_q \varepsilon_t - q, \tag{5}$$

where $\{\varepsilon_t\}$ is a Gaussian white noise series with zero mean and variance σ_z^2, and $\{\alpha_i\}, \{\beta_i\}, i = 1, 2, \ldots, n$, are constants (parameters to be estimated).

The theory of time series analysis, and in particular of ARMA models, is a useful tool for analysing, modelling and forecasting wave data. Thus, it has received considerable attention in the literature of ocean engineering for the last decades. Spanos [7] presented extensively the three different algorithms for AR, MA and ARMA models in order to simulate time series which are compatible with a given power spectrum of ocean waves, also describing their applicability to offshore engineering problems. Li and Karrem [8] simulated the wave processes and wave height fluctuations of given time histories by ARMA algorithms. Analysis of measured water surface records in Sobey [9] suggested that sequences of individual waves can reasonably be described as first order ARMA processes. Guedes Soares and Fereira [10] used the Box – Jenkins autoregressive models to simulate time series of significant wave height. Stefanakos and Athanassoulis [11] and Ho, Yim [12] applied ARMA models for the analysis, completion and simulation of non-stationary time series of wave spectral parameters with missing values. Another method, based on a different concept, was presented in Özger [13]; the method combined artificial neural networks, fuzzy logic and ARMA models and it was employed for significant wave height forecasting.

The aim of this work is, by using Box-Jenkins methodology [14], to describe and model the time series of the sse $\eta(t)$, and identify the most appropriate ARMA model. An additional issue of this work is to examine any potential relation between the specific ARMA models selected and the spectral parameters of the corresponding sea-states, i.e. significant wave height H_S, main direction θ_W, spectral peak period T_P, as well as the spectral bandwidth parameters ε and ν.

An application of the modelling of $\eta(t)$ is related to the control of specific type wave energy converters. Specifically, the efficient forecast of the sse is directly connected to the optimization of the efficiency of wave energy extraction (Fusco and Ringwood [15]).

The structure of this work is the following: in Section 2 the main steps of the implemented methodology for the estimation of an ARMA model are presented and discussed. In Section 3, the wave data source is described and the statistical analysis of the corresponding sea-state spectral parameters is presented. In Section 4, the numerical results obtained in this work are provided and analytically discussed. Finally, in Section 5 concluding remarks are provided along with some suggestions for further research.

2. Methodology for building ARMA models for $\eta(t)$

2.1. Introduction

The best-fitting time series analytic model for the description of the process of sse is investigated following the Box-Jenkins methodology [14,16]; in this section, this method will be described in brief. There are three main steps in developing a time series model according to Box-Jenkins methodology: i) identification, ii) estimation, and iii) validation. Provided that the examined time series is zero-mean and covariance-stationary, the Wold decomposition (or representation) theorem guarantees the existence of an ARMA model for the approximation of the time series.

2.2. Identification

At the identification stage, the main aim is to determine if the examined time series is stationary (in order for the Wold decomposition theorem to be valid). Moreover, a time series may be also exhibit seasonality that should be also modelled. As a first step any linear trend in the series should be removed. Both non-stationarity and seasonality can be identified using the sample autocorrelation function (ACF) of the time series, i.e.,

$$\hat{\rho}(h) = \frac{\hat{\gamma}(h)}{\hat{\gamma}(0)}, \tag{6}$$

where

$$\hat{\gamma}(h) = \frac{1}{n} \sum_{t=1}^{n-|h|} \left(x_{t+|h|} - \bar{x}\right)(x_t - \bar{x}), \quad -n < h < n, \tag{7}$$

is the sample autocovariance function and

$$\bar{x} = \frac{1}{n} \sum_{t=1}^{n} x_t, \tag{8}$$

is the mean value of the time series.

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