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Beyond significant wave height: A new approach for validating spectral wave models

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ABSTRACT

Wave data are required in many engineering applications. At locations where measured records are not available or are too short for design purposes, estimates of wave properties from numerical wave models are often used to characterise the expected wave climate. Typically, model predictions are validated against observations of the sea-state parameters, such as significant wave height, peak wave period, mean wave period and mean wave direction. However, while agreement between observed and predicted sea-state parameters can be good, in some cases the measured and predicted wave spectra can diverge significantly. In these circumstances, simple sea state parameters alone are not sufficient to describe the range of wave conditions that could arise at a given site. In this paper we present a new, alternative approach for assessing wave model performance by applying new parameterisation to the frequency wave spectrum. Seven parameters (significant wave height, peak frequency, peak energy density, squared Euclidean distance, skewness, kurtosis and mean width deviation) are used to better define the characteristics of unimodal wave spectra. Sensitivity tests are undertaken to analyse the performance and sensitivity of these parameters in identifying differences between observed and predicted wave spectra, using a range of idealised JONSWAP wave spectra. We demonstrate that comparing multiple parameters is a better method to distinguish differences between spectra than the results obtained using individual parameters in isolation. As such, application of two-dimensional validation matrices are proposed to provide a better, qualitative overview of the goodness of fit between observed and predicted wave spectra. The advantages of the new approach are demonstrated through validation of a hindcast spectral wave model at Hastings, southeast England. We believe that we have achieved our purpose here to start a discussion on alternative validation techniques that could be enhanced in the future.

1. Introduction

Wind-generated waves can induce strong, destructive forces on structures in the coastal and marine environment. To be effective, coastal defences, platforms, pipelines and offshore wind farms must resist wave loading. Thus, wave data are required to define the operational and extreme wave conditions that might be expected at a given site (Goda, 1985). However, systematic wave recordings are rare and relatively short in most parts of the world. In offshore areas, historical wave records from ship-mounted instruments and from wave buoys are scarce. In coastal areas, wave data are more widely available, but most of the existing records span a short period, typically less than 10 years (e.g., Mason et al., 2008). Evaluation of design wave conditions for extreme events requires a much longer period of measurement (30 years or more is required to represent a wave climate). In recent years, satellite altimeter data have been used to measure wave heights (e.g. Young, 1999) but these data are not suitable for local studies because of the intermittent nature of the records and the limited spatial resolution (Krogstad and Barstow, 1999).

To address these problems, recourse is frequently made to spectral wave modelling to derive synthetic wave climate information to assist the design processes. Suitable spectral wave models have been developed to compute the spectral growth and transformation of swell waves and wind waves at sea (e.g. Tolman, 2009). Spectral wave outputs can be extracted at any point in the model domain, and used in areas where measured wave records are not available. Models can provide, for example, the input required for the design of marine structures that are subjected to cyclic wave loadings or to study the motion response of marine vessels (Shaw, 1999).

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In all cases, model validation against measured wave records is crucial to ensure the accuracy and reliability of spectral wave models. Generally, the approach adopted has been to compare the following measured and predicted sea-state parameters: (1) significant wave height, (2) wave periods like peak period, mean period, zero-crossing period, and energy-averaged mean period, and (3) mean wave direction (Holthuijsen, 2007). However, these parameters alone are not sufficient to characterise all the properties of the wave spectrum. In certain cases, it is possible for sea-state parameters from a wave model and from measurements to be in good agreement, even when the measured and predicted spectral shapes diverge from one another. Misrepresentation of the wave spectra in wave models could lead to engineering failure with ensuing damage and potential threat to human lives. As such, there is a need to develop better approaches that ensure wave model spectra are as close as possible to the measured spectra — in magnitude, position and shape.

The aim of this study is to discuss a new approach for validating spectral wave models by applying new parameterisation to the frequency wave spectra. The new validation approach should be able to: (a) facilitate easy inter-comparison between wave spectra characteristics; (b) provide a robust comparison approach that is not limited to specific spectral conditions; and (c) provide a quick and easy representation of how well the energy distribution has been predicted.

This aim is addressed in five main stages. First, we identify existing parameters used in wave mechanics and other related disciplines for defining the characteristics of wave spectra and other continuous distributions (Section 2). Secondly, we carry out an objective assessment of the performance of the parameters, both individually and collectively for describing the characteristic differences between two wave spectra (Section 3). Thirdly, we define an additional parameter to better represent the spectral widths in wave spectra (Section 4). Fourthly, we propose the application of 2D validation matrices for an improved qualitative assessment of spectral wave model performance (Section 5). Lastly, we demonstrate the new suggested approach through validation of output from a real wave model (Section 6). The scope of the study covers the analysis of frequency wave spectra only. Directional wave spectra are excluded at this stage because of their higher level of complexity. Our purpose in this paper is not to propose a radical and exhaustive new validation approach, but to start a discussion on alternative validation techniques that will hopefully benefit the wave modelling community and related end users.

Table 1
List of SWPs adopted from wave mechanics or other disciplines.

No	Parameter	Definition	Origin/example of application
1	Significant wave height, H_s	Introduced by Sverdrup and Munk (1947) as the mean height of the highest one-third of observed waves within a record. Estimated as following: $H_s = 4\sqrt{m_0}$ (1) where m_n is the n^{th} moment of the frequency wave spectrum, calculated as: $m_n = \int_0^\infty f^n E(f) df$ (2) where E is the spectral energy density and f is the discretised frequency.	Wave mechanics
2	Peak energy density, E_{max}	Maximum spectral energy density in the frequency domain	Wave mechanics
3	Peak frequency, f_p	Frequency corresponding to the peak energy density, E_{max}	Wave mechanics
4	Mean wave period, T_m	Estimated from wave spectrum (e.g. MIKE by DHI, 2014) as following: $T_m = \frac{m_0}{m_1}$ (3)	Wave mechanics
5	Zero-crossing period, T_z	Estimated from wave spectrum (e.g. MIKE by DHI, 2014) as following: $T_z = \sqrt{m_0/m_2}$ (4)	Wave mechanics
6	Energy averaged mean period, T_{-10}	Estimated from wave spectrum (e.g. MIKE by DHI, 2014) as following: $T_{-10} = \frac{m_{-1}}{m_0}$ (5)	Wave mechanics
7	Spectral width parameter, ε	Root mean square (RMS) width of the frequency wave spectrum. Cartwright and Longuet-Higgins (1956) suggested the following relationship: $\varepsilon = \sqrt{\frac{m_0 m_4 - m_2{}^2}{m_0 m_4}}$ (6)	Wave mechanics
8	Spectral peakedness parameter, Q_p	Alternative to spectral width parameter, suggested by Goda (1974): $Q_P = \frac{2}{m_0{}^2}\int_0^\infty f E^2(f) df$ (7)	Wave mechanics
9	Skewness, Sk	Third central moment of a wave spectrum: $Sk = \frac{\sum E(f)(f-f_m)^3}{f_{sd}{}^3}$ (8) where f_m is the mean spectral frequency and f_{sd} is the standard deviation	Probability and statistics; particle size distribution (Blott and Pye, 2001)
10	Kurtosis, K	Fourth central moment of a wave spectrum: $K = \frac{\sum E(f)(f-f_m)^4}{f_{sd}{}^4}$ (9)	Probability and statistics; particle size distribution (Blott and Pye, 2001)
11	Squared Euclidean distance, D_{SE}	Measure of distance between two spectra: $D_{SE} = \int_0^\infty [E_o(f) - E_p(f)]^2 df$ (10) where E_o and E_p are the spectral energy density of the observed and predicted spectra	Acoustic signal processing (Helén and Virtanen, 2007)
12	Kullback–Leibler divergence, D_{KL}	Non-symmetric measure of distance between a “real” probability distribution function, p and the “approximating” probability distribution model, q (Kullback and Leibler, 1951): $D_{KL}(p,q) = \int_0^\infty ln\left(\frac{p(x)}{q(x)}\right) p(x) dx$ (11) The above equation has been modified to measure distance between wave spectra: $D_{KL}(E_o, E_p) = \int_0^\infty ln\left(\frac{E_o(f)}{E_p(f)}\right) E_o(f) df$ (12)	Theory of information
13	Kolmogorov–Smirnov distance, D_{SE}	Maximum distance between a cumulative frequency distribution function and the observed cumulative step-function (Massey Jr., 1951). The original equation has been modified to measure goodness of fit between two wave spectra, expressed as a percentage: $D_{KS} = Max\lvert C_o(f) - C_p(f)\rvert$ (13) where C_o and C_p are the cumulative spectral energy of the observed and predicted spectra respectively.	Probability and statistics