AUTOMATIC WAVE MODEL CALIBRATION USING SURROGATE MODELS

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INTRODUCTION

Alonso and Solari (2017) presented an approach for the automatic calibration of a third-generation wave model, using the significant wave height error as the objective function. Alonso and Solari (2021) extended the methodology, incorporating a spectral error as the objective function and the use of the maximum dissimilarity algorithm to minimize the number of sea states used for calibration without losing representativeness. It was found that the use of the spectral error does not necessarily guarantee an improvement in Hs results. Furthermore, calculation times were still too long for the general application of the method.

The objective of this work is twofold: (1) to introduce the use of surrogate models in the automatic calibration algorithm to speed up computation times, and (2) to explore a wide spectrum of objective functions for model calibration.

METHODOLOGY

Following the work of Zhou et al (2018), the use of a surrogate model is incorporated into the calibration process. The surrogate model approximates the input-output relationship of the third-generation wave model by fitting over a set of evaluated training samples that is systematically enlarged throughout the calibration process. In this case, a Gaussian process is used as a surrogate model (Rasmussen and Williams 2006).

Objective functions based on the use of two or three wave parameters (height, period, and direction), as well as based on the full wave spectra, were explored. In both cases quantitative error functions as well as functions based on the concept of Limits of Acceptability (Vrugt and Beven 2018) were used.

For the selection of which model parameters to calibrate, we follow what is presented in Alonso and Solari (2021).

RESULTS

The use of the surrogate model made it possible to reduce the computational times required for automatic model calibration by approximately two orders of magnitude. This not only facilitates the systematic application of the methodology in practice but also made it possible to explore a wide range of objective error functions. In this regard, it was found that the most promising results are obtained with objective functions that use the error in two or more wave parameters, both when using quantitative errors and when using LoA (Table 1; Figure 1).

REFERENCES

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Table 1 - RMSE obtained for several of the error functions tested.

RMSE	Hs [m]	Tm [s]	Dm [º]
Default	0,18	1,6	38
Error Hs and Dm	0,23	1,0	20
LoA Hs and Dm	0,23	1,2	24
Error Spectre	0,20	1,5	30
LoA Spectre	0,39	2,5	23

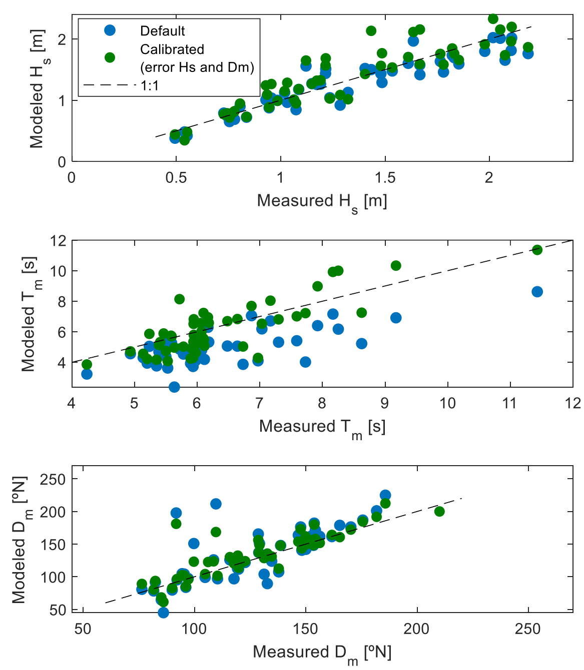

Figure 1 - Comparison of model results in default configuration and calibrated using objective function base on Hs and Dm errors.