# DATA-DRIVEN DYNAMIC MODELS FOR SPATIAL INTERPOLATION OF WAVE ENERGY SOURCE CHARACTERISTICS: PRELIMINARY EXPERIMENTAL VALIDATION

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## INTRODUCTION

World energy demand has increased significantly over recent decades, making clean and efficient energy production one of the most crucial challenges. In the context of renewable energy, wave energy coming from ocean and sea waves has emerged as one of the most promising sources, having a vast (yet untapped) potential (Astariz (2015)) of around 32 000 TWh/year (Mork (2010)). In contrast to other renewable energy technologies, such as wind or solar, technology convergence has been slow among wave energy converters (WECs). Among the challenges is the variability of the wave energy resource itself, with variations in amplitude and period, and directionality (Li (2021)). For this reason, accurate knowledge of metocean data is of paramount importance before installation for site selection, productivity assessment, and structural design; data are also crucial for installation, operation, maintenance and decommissioning. The metocean datasets needed to establish the correct deployment site must be comprehensive enough in terms of number, accuracy, time length, and breadth in space of the measurements. However, to obtain such amount and quality of data, extensive in-situ surveys (made through the installation of data buoys) are needed years before plant deployment and during operations, delaying the actual activities and demanding significant capital expenditure. In the presented work, a survey campaign is simulated in the wave basin facility at Aalborg University, Denmark. The obtained data are used to build dynamic models employed to estimate the wave source characteristics, assuming that, after an initial learning stage, most of the in-situ instrumentation is uninstalled and not available, and for this reason the remaining information must be obtained differently. Linear and nonlinear dynamic models are employed for this purpose, and compared on a validation set to assess their estimation capability.

## EXPERIMENTAL SETUP

The tests were conducted at the wave basin facility available at the Ocean and Coastal Engineering Laboratory in Aalborg University. The available basin has dimensions of 19.3 [m] x 14.6 [m] x 1.5 [m] (length x width x depth), with an active area of 13 [m] x 8 [m] (length x width). The wave tank is equipped with a state-of-the-art long-stroke segmented wavemaker system, with active absorption, and composed by 30 individually controlled wave paddles. During the tests, concrete blocks placed on the tank floor are employed to simulated an abrupt change in bathymetry, while 19 wave gauges are recording the wave elevation, simulating in-situ measurements instrumentation. Waves are generated, continuously (but slowly) changing their spectrum following real data recorded in the site of DanWEC, at Hanstoholm in the North Sea (Brodersen (2013)). Two months of sea conditions were simulated (with a scaling factor of 1:200) in the basin, replicating the same conditions measured in the DanWEC site. In the area surrounding the concrete blocks, 19 wave gauges were placed to measure the resulting wave elevation. These wave gauges were employed to simulate in-situ instruments, all available at the beginning of the survey campaign, and then to produce the validation set for the dynamic models tested in this work. A picture of the experimental setup is shown in Figure 1. The data coming from the wave elevation measurements sampled at 200 [Hz] are then postprocessed to obtain a sequence of significant heights Hs, and energetic periods Te, employed to build the data-driven models.

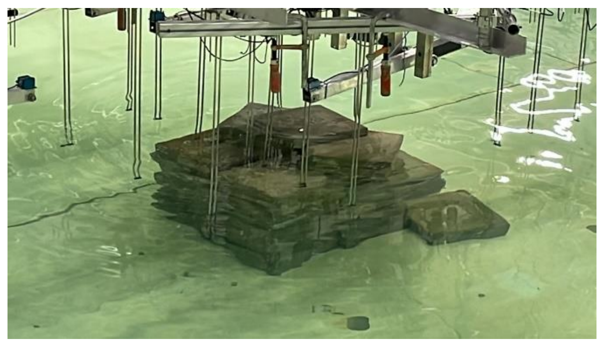

Figure 1 - Experimental setup employed to simulate the wave source survey inside the Aalborg University wave basin facility.

## DATA-DRIVEN MODELS: LINEAR MIMO SYSTEMS

In this work, we decided to consider the dynamic systems that describe each of the two wave source characteristics measured (Te and Hs) as multi-input multi-output (MIMO) systems, in which the set of inputs are the available in-situ instruments still available after the initial training time, while the rest are outputs to be estimated. More in particular, from the initial 19 wave gauges, we consider available, after this initial period, only 5 of them, and consider the rest as outputs. This results, in the linear discrete model case, in a MIMO system like the one in Equation 1:

$$\begin{bmatrix} Hs_6(t) \\ \vdots \\ Hs_{19}(t) \end{bmatrix} = \theta \begin{bmatrix} Hs_1(t) \\ \vdots \\ Hs_1(t-n) \\ \vdots \\ Hs_5(t) \\ \vdots \\ Hs_5(t-n) \end{bmatrix}, \tag{1}$$

Where the subscripts is used to indicate the wave gauge ID number, and the convention $Hs_6(t)$ indicates, e.g., the significant height at $t$ time instant in the position of the 6-th wave gauge, while θ indicates the matrix of the parameters that must be identified from the data through a proper system identification process (Ljung, 1999). As it is possible to see in Equation 1, from the input wave gauges, up to $n$ previous sea state conditions are employed between the inputs, to properly build a dynamic MIMO model of $n$ order. In this work, after several attempts, we decided to work with $n$ = 10, to maintain a proper trade-off between the level of complexity and accuracy of the identified model. In the nonlinear case, we decided to model the same relation (with the same set of inputs and outputs), by means of a feedforward neural network, with 4 hidden layers of 15 neurons each (Schoukens, 2019). The activation functions of the layers inside these neurons are Rectified Linear Unit (ReLU) functions, to attempt at modelling the possible nonlinearities characterizing the system, and the training algorithm is the Adam one .

## PRELIMINARY RESULTS

In the training process, among the two months that have been simulated, the first two weeks are employed as training set, while the remaining weeks constitute the validation set over which the validation performance have been computed. It is important to notice that in all the tests that have been conducted, the significant heights measured among the 19 wave gauges can vary up to 60%, while the energetic period up to 10%, due to the change in bathymetry. To assess the robustness of the methodology, 10 different models have been made with different (random) combinations of input and output gauges. To compute the validation performance, for each model, an average normalized root mean square error (aNRMSE) is computed among the different output gauges. Considering the significant height, with the linear MIMO model described above, the aNRMSE is, in average (between the 10 different random configurations) 81.3% (with peaks of 88.9% in a configuration that suitably span the space of wave gauges around the concrete blocks, and lows of 75.4%). The nonlinear MIMO model is capable of higher accuracy results. This kind of model is able to obtain NRMSE in average of 88.7% (with peaks at 93.0% and lows at 79.1%). These results demonstrate the better capabilities of nonlinear models in describing the nonlinear effects that can be caused by the abrupt change in the bathymetry, by adding nonlinear contribution that can characterize the wave source dynamic system. Similar results are obtained with the energy period (80.0%/87.9%/77.2% vs. 86.5%/90.2%/78.2%).

## CONCLUSIONS

The proposed work shows the preliminary results of the experimental validation of data-driven dynamic models employed to model the wave source. This kind of models, purely based on measured data, can, potentially, be used to model the wave source, potentially addressing part of the issues of metocean surveys, by properly interpolating in time and space the resource. Further investigation can be made, trying to better refine the model structures (in terms of order and activation functions), and trying to reduce the number of available in-situ measurements after the training stage.

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