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Prediction and optimization of wave energy converter arrays using a machine learning approach

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A R T I C L E I N F O

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A B S T R A C T

Optimization of the layouts of arrays of wave energy converters (WECs) is a challenging problem. The hydrodynamic analysis and performance estimation of such systems are performed using semi-analytical and numerical models such as the boundary element method. However, the analysis of an array of such converters becomes computationally expensive, and the computational time increases rapidly with the number of devices in the system. As such determination of optimal layouts of WECs in arrays becomes extremely difficult. In this paper, a methodology involving multiple optimization strategies is presented to arrive at the solution to the complex problem. The approach includes a statistical emulator to predict the performance of the WECs in arrays, followed by an innovative active learning strategy to simultaneously explore and focus in regions of interest of the problem, and finally a genetic algorithm to obtain the optimal layouts of WECs. The method is extremely fast and easily scalable to arrays of any size. Case studies are performed on a wavefarm comprising of 40 WECs subject to arbitrary bathymetry and space constraints.

1. Introduction

Arrays of wave energy converters (WECs) have been extensively studied in the literature starting with the pioneering work of [1]. Notably, Budal [1] used the point-absorber approximation which assumes the dimensions of the WECs are much smaller than the wavelength of the incident wave field and therefore the diffracted wave field can be considered to be negligible. Since then, advances in numerical and analytical techniques (see e.g. Refs. [2–5]) in the analysis of wave-structure interactions have enabled the investigation of the behavior of arrays of WECs of arbitrary shapes, taking into account the effects of both the diffracted and the radiated wave fields. Numerical boundary element codes (e.g. NEMOH and WAMIT developed at Ecole Centrale de Nantes and MIT, respectively) are widely used to understand the effects of the hydrodynamic interactions and to quantify the performance of the WECs and the array as a whole. However, such methodologies involve increased computational cost and resources. The general objective is to understand the effect of the interactions on the performance of the WECs and to determine layouts which would maximize the power captured from the whole system. In order to quantify the effects of the interactions on the performance of the array, Budal [1] defined the q factor which is the ratio of the net power captured (ideally the maximum possible) by the array to the power absorbed by the same number of WECs in isolation. Budal [1] observed that it is possible to have q factors much larger than 1 for particular wave frequencies. But the peaks in the q factor are accompanied with wide troughs in its variation, and since a real ocean is polychromatic, Budal suggested that a properly designed array configuration should minimize the effect of the destructive influences. However, the identification of optimal layouts for a particular wave-climate is still a big challenge. The complexity of the optimization problem is manifold. The number of WECs in arrays can vary from one site to another, and separate optimizations needs to be performed in each case. Every single evaluation of the numerical/semi-analytical models has a computational cost which increases with the size of the array. In addition, there can be various constraints to such a problem (e.g. bathymetry variations for nearshore WECs). Child and Venugopal [6] presented a parabolic intersection method and a genetic algorithm to arrive at the

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optimal layouts of arrays. While the parabolic intersection approach uses simple calculations for a quick estimate of the array layouts, the genetic algorithm requires many evaluations of a semi-analytical (or numerical) method which is computationally expensive. Such a direct application of sequential optimization techniques also implies that if the number of WECs is changed, a new set of evaluations needs to be computed and analysed. In this work we propose a fast and scalable approach to address the challenge of determining the best layout for any number of WECs and arbitrary bathymetry constraints. We first use an active learning strategy to train a statistical emulator of the individual WECs inside the array. We then predict the performance of the whole wavefarm by evaluating only the quasi-instantaneous emulator. The optimization of the layout under the various constraints is then performed on the predicted performances with a genetic algorithm designed specifically for this task.

The analysis in this work is performed on a well known WEC-the Oscillating Wave Surge Converter. A number of studies are now available which have looked at various aspects of the device (see e.g. Refs. [7,8]). Most recently, a mathematical model was developed in Ref. [9] to analyse the behavior of the OWSCs in a wave farm and the simulations in this work will use this model. The overall performance of the array is decomposed as the sum of the powers captured by each individual WEC. In a realistic scenario, the seas are highly irregular, and the interaction effects on a particular WEC due to WECs located away from it are largely diminished. It is reasonable to assume that individual WECs in an array are predominantly influenced by those located very close to them. Our approach targets the approximated performance where we simplify the model of the individual WECs in order to take into account only a limited number of interactions. A WEC located inside the array is strongly influenced by the two WECs which are nearest to it, i.e. one on each side (see Fig. 2). To model the behavior of such a WEC, we consider a 3-WEC cluster and focus on the behavior of the central WEC. On the other hand, the edge WECs are modelled using a 2-WEC cluster.

Our prediction function is based on Gaussian process regression trained with an active learning strategy, the Gaussian Process Upper Confidence Bound with Pure Exploration algorithm (GP-UCB-PE) [10]. Since the final goal of the work is to determine optimal layouts of an array, we are more interested in layouts which result in good performance of the individual WECs. The active learning strategy determines sequentially which configurations of the 3-WEC and 2-WEC clusters should be evaluated aiming to improve the predictions of the optimal clusters using the least number of evaluations possible. The algorithm performs a trade-off between exploitation and exploration looking for the maximum while exploring clusters with high uncertainty.

In our optimization methodology, we incorporate some constraints which are relevant to the problem. The OWSCs are near-shore WECs with depth specific designs, and as such bathymetry will play a significant role in deciding their locations. We consider an upper and a lower bound on the bathymetry contours, within which the placement of the centre of the OWSCs is restricted. Although the mathematical model (for simulations) is based on a constant water depth assumption, the bathymetry constraints in the optimization problem take account of the spatial limitations imposed by the depth variations at real locations, in the placement of the WECs. In a practical situation, proper utilisation of space is also an important consideration and to account for that an upper bound in the distance separating the centres of the first and the last WEC in the y' direction (see Fig. 1) is fixed at a particular value.

The methodology of the simulations, statistical emulator and the machine learning algorithm will be illustrated in the following sections. Later in §5, case studies are performed on the optimization of a wavefarm comprising of 40 OWSCs, followed by discussions and conclusion.

2. Simulation model

The simulations for the various layouts are performed using the mathematical model of [9]. A wavefarm comprising of M WECs (see Fig. 1) is considered, and so the 2 M variables that need to be optimized are $x'_1, y'_1, \ldots x'_M, y'_M$, which are the horizontal coordinates of the centres of the OWSCs in the x' and y' directions respectively.

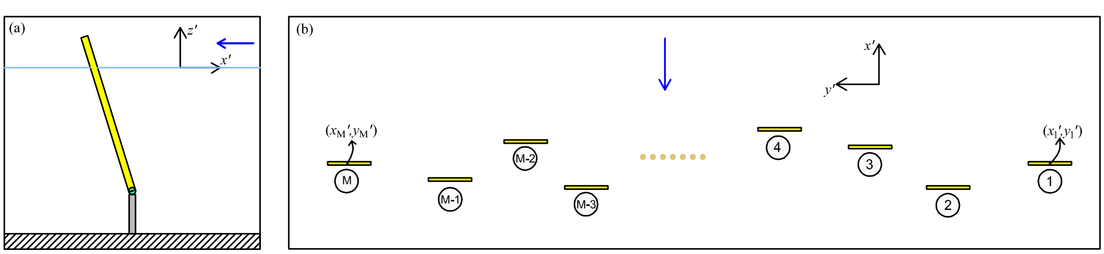

Fig. 1. Geometry of the physical system (a) side view of one of the WECs (b) top view of a wavefarm comprising of M WECs. The right most OWSC is considered to be the first WEC, with the numbering increasing towards the left. The horizontal spatial coordinates of the centres of the OWSCs are: (x'_1, y'_1), (x'_2, y'_2), ……, (x'_M, y'_M).

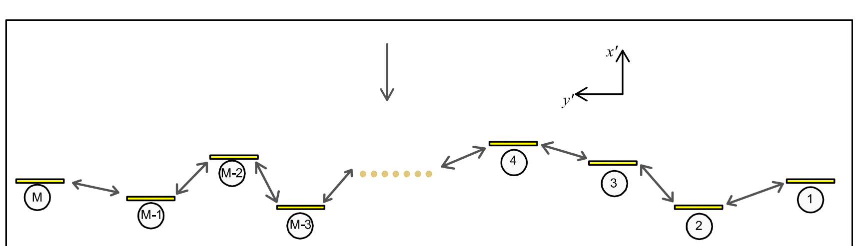

Fig. 2. The methodology considers only the interaction of the WECs with their neighbouring ones. As such the two edge WECs located at the two extremes of the wavefarm can be modelled with a simplified 2-WEC cluster configuration while those lying in the interior with a 3-WEC cluster arrangement. The right most OWSC is considered to be the first WEC of the array. The horizontal spatial coordinates of the centres of the OWSCs are: (x'_1, y'_1), (x'_2, y'_2), ……, (x'_M, y'_M).