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UNCERTAINTY AND SENSITIVITY IN WAVE ENERGY CONVERTER ARRAYS: SPARSE POLYNOMIAL CHAOS EXPANSION OF LAYOUT–PTO–WAVE EFFECTS

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ABSTRACT

Designing wave energy converter (WEC) arrays requires coordinated decisions regarding spatial configuration, power-take-off (PTO) settings, and the incident wave climate. This paper quantifies the relative contribution of these three factor groups to array power performance for a seven-device system using non-intrusive Polynomial Chaos Expansion (PCE). A linear hydrodynamic model with full device–device coupling is used to generate training data for total absorbed power and array interaction factor under irregular JONSWAP sea states. Uncertain inputs include layout parameters (longitudinal spacing and transverse offset), PTO parameters (linear damping and stiffness about the dominant mode), and wave parameters (significant wave height and peak period). Sparse PCE surrogates up to third order are constructed using least-angle regression (LARS), and variance-based global sensitivity indices, including first-order, total-order, and selected second-order Sobol' terms, are evaluated. Results for the seven-WEC case study indicate that wave parameters, particularly significant wave height and peak period, dominate variability in array power output, while PTO damping represents the leading controllable influence on energy absorption. Spatial configuration contributes through hydrodynamic interaction effects, with longitudinal spacing emerging as the most influential layout parameter. The PCE surrogates accurately reproduce high-fidelity model responses with low approximation error, enabling rapid parametric exploration and efficient design screening focused on power performance. The proposed framework provides a transparent attribution of power performance drivers across layout, PTO, and wave climate for multi-device WEC arrays. From a practical perspective, the results highlight where tuning effort is most effective, support prioritization of key design variables, and offer guidance for reducing the dimensionality of the design space by focusing on parameters that explain the majority of variance in absorbed power.

Keywords: wave energy converters; surrogate models; multi-device arrays; ECHOWAVE dataset; polynomial chaos expansion

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1. INTRODUCTION

Wave energy represents a vast and largely untapped renewable resource with the potential to contribute meaningfully to future low-carbon energy systems [1]. Despite sustained research activity over recent decades, the commercial deployment of wave energy converter (WEC) technology remains limited when compared to more mature renewables such as wind and solar [2, 3]. Recent studies indicate that integrating wave energy farms with existing offshore wind and solar infrastructure could increase overall energy yield while reducing shared installation and operational costs, thereby improving economic viability [4]. Realizing this potential, however, requires advances in both device-level design and array-level optimization.

To date, much of the research on wave energy systems has focused on the performance of individual WECs, with comparatively less attention devoted to the collective behavior of multiple devices operating as an array. In practice, array layouts are often designed conservatively to minimize hydrodynamic interactions between neighboring devices, effectively treating interaction effects as detrimental. This approach may lead to suboptimal utilization of the available wave resource [4]. A more systematic understanding of how spatial configuration, power-take-off (PTO) characteristics [5], and wave conditions jointly influence array power output is therefore essential for improving overall performance. Importantly, no single array configuration can be expected to perform optimally across the full range of wave conditions encountered over a device's operational lifetime, underscoring the need for design methodologies that explicitly account for environmental variability.

The challenge of WEC array design is compounded by two key factors. First, the spatial arrangement of devices strongly affects hydrodynamic interactions and, consequently, power absorption at the array level, making layout selection a critical design variable. Second, wave climates are inherently stochastic and exhibit significant variability over time, particularly when considered over multi-decadal horizons relevant to commercial

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projects. Studying the combined influence of these factors requires a large number of simulations spanning a wide range of configurations and wave conditions. High-fidelity hydrodynamic models, while accurate, are computationally expensive and therefore impractical for large-scale probabilistic analyses and iterative design studies [6].

To overcome these limitations, surrogate modeling techniques have emerged as an effective means of approximating complex numerical models at a fraction of the computational cost [7, 8]. Among these, Polynomial Chaos Expansion (PCE) offers a systematic framework for representing model outputs as functions of uncertain inputs and for quantifying the contribution of individual parameters to output variability. PCE-based surrogates are particularly well suited for probabilistic performance assessment, as they enable efficient evaluation of statistical moments and global sensitivity indices without repeated calls to the underlying high-fidelity model (Stavropoulou et al., 2023). However, most existing applications of PCE to WEC array analysis have been limited to fixed spatial configurations, with uncertainty considered primarily in the environmental or device parameters, thereby restricting the ability to assess the combined influence of layout and wave variability on array power performance [9].

In this paper, a non-intrusive PCE framework is applied to quantify the relative influence of spatial configuration, PTO parameters, and wave characteristics on the power performance of a seven-device WEC array. Training data are generated using a linear frequency-domain hydrodynamic model with full device–device coupling [6], and the surrogate is constructed over a probabilistic wave dataset representative of long-term operating conditions derived from the ECHOWAVE hindcast [10]. The focus is restricted exclusively to power-related metrics, including total absorbed power and array interaction effects. By combining sparse PCE techniques with variance-based global sensitivity analysis, the proposed approach provides clear insight into the dominant drivers of array power variability while enabling rapid parametric exploration. The methodology is general and can be applied to other wave datasets and array configurations, providing a foundation for future array layout optimization studies under realistic and uncertain wave climates.

2. METHODOLOGY

This section describes the numerical and surrogate modeling framework (see Figure 1) adopted to assess the power performance of a seven-device wave energy converter (WEC) array under uncertain environmental and design conditions. The approach combines a linear hydrodynamic model developed using Capytaine [11, 12] with power calculations implemented within the WEC-Sim [13] framework, and a non-intrusive Polynomial Chaos Expansion (PCE) surrogate to enable efficient probabilistic analysis and global sensitivity assessment.

2.1. Overview of the Modelling Framework

The overall methodology Figure 1 follows a data-driven surrogate modeling approach consisting of four main stages:

1. definition of uncertain wave, power-take-off (PTO), and spatial configuration parameters;

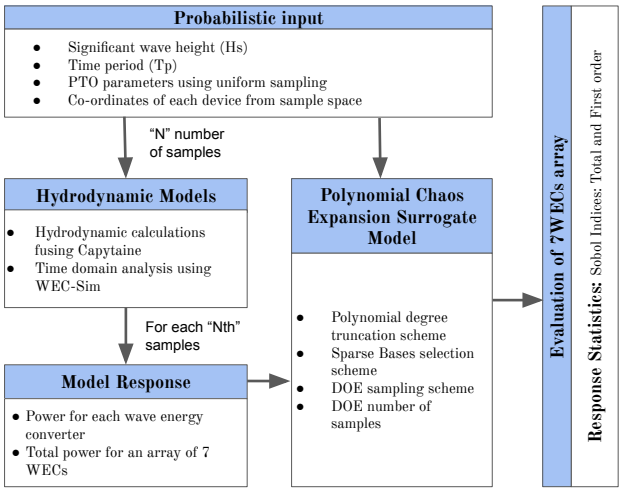

FIGURE 1: Flowchart showing steps for creating a surrogate model for evaluation of wave energy converter arrays.

2. generation of training data using a high-fidelity hydrodynamic model;

3. construction of a sparse PCE surrogate;

4. post-processing of the surrogate to compute statistical moments and variance-based sensitivity indices.

Unlike previous PCE-based studies [9, 14] of WEC arrays, which typically considered fixed spatial configurations, the present framework explicitly includes array layout parameters as uncertain inputs. This enables simultaneous assessment of environmental variability and array design variability within a unified surrogate modelling framework.

2.2. WEC Array Description

The system under consideration is a seven-device array composed of identical floating point absorber type WECs. Each device (spherical: diameter 'D' of 10 m) operates primarily in heave and is assumed to be axisymmetric. The geometric details of the device are described in detail in [9, 14]. The array layout is chosen according to sampling scheme shown in Figure 2 and Figure 3. All devices are assumed to be identical in geometry.

2.3. Definition of Uncertain Inputs

Three groups of uncertain input parameters are considered. Firstly, the wave parameters in terms of significant wave height H_s and peak period T_p, derived from a long-term probabilistic wave dataset representative of site-specific operating conditions are considered (see Figure 2). Secondly, PTO parameters are defined over practical tuning ranges in terms of linear damping coefficients. Lastly, the spatial configuration parameters are considered in terms of spatial co-ordinates of each device drawn from the configuration space shown in Figure 3. Seven random points were drawn maintaining conditions of average pairwise distance as shown in Figure 3 and minimum distance of at least 30m between devices. The minimum distance between the devices is set to 30 m (3 times D) based on the practical guidelines

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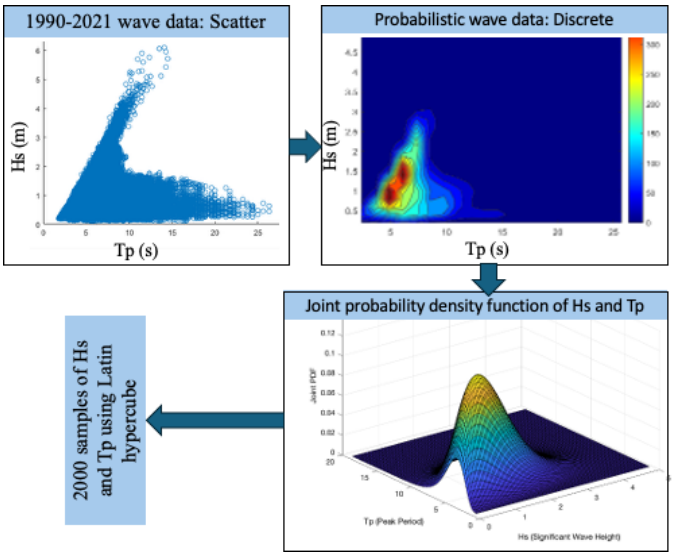

FIGURE 2: Process to sample H_s and T_p from ECHOWAVE dataset.

for maintenance and operation. Moreover, as mentioned in the literature [15] the interactive effects may start to appear as early as for the spacing of 6 times the diameter (D), which is much higher than the considered minimum spacing of 3D.

PTO and spatial configuration parameters are modelled as statistically independent random variables with uniform probability distributions over their prescribed ranges, enabling systematic exploration of the combined design–environment space.

2.4. Design of Experiments and Training Dataset

A space-filling design of experiments is employed to sample the joint input space of wave, PTO, and layout parameters. For each sampled realization, hydrodynamic coefficients are computed using Capytaine and passed to WEC-Sim to evaluate array power output. The resulting dataset constitutes the training data for the surrogate model. This non-intrusive approach allows the surrogate to be constructed without modification of the underlying hydrodynamic or power performance solvers and enables efficient parallel computation of the training dataset.

2.5. Polynomial Chaos Expansion Surrogate

The advantages of Polynomial Chaos Expansion (PCE) models as opposed to other surrogate model approaches are several. Firstly, these models are non-intrusive and do not require any modification to the underlying FD simulations. Secondly, PCE models are transparent in terms of the theoretical underpinnings of their performance. Lastly, the post-processing of PCE model coefficients provides analytically computed Sobol indices, which can be used for global sensitivity analysis.

The PCE model in this work is built using UQlab, a framework [16, 17]. This framework provides a high-level implementation of Uncertainty Quantification analysis. A hyperbolic (q-norm) polynomial degree truncation scheme [18] with $q = 0.75$ was chosen in the search of optimal basis. The other details regarding PCE parameters can be found in [19].

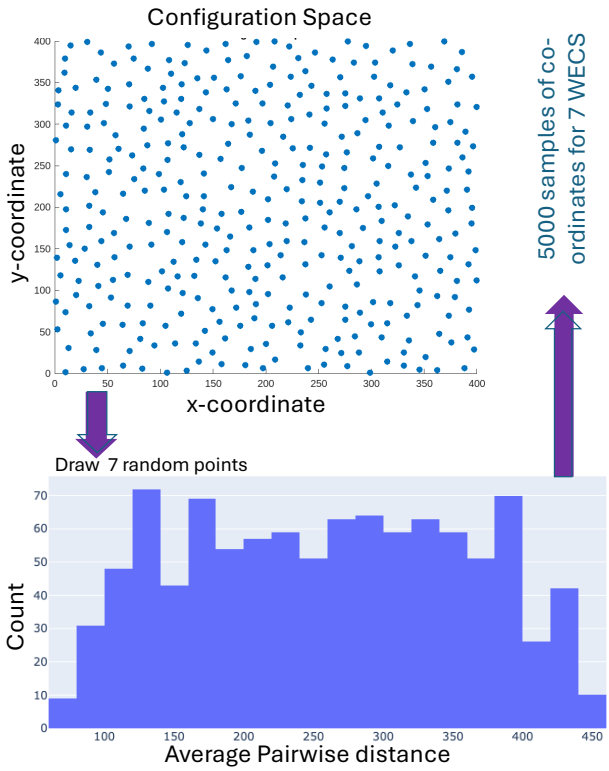

FIGURE 3: Sampling scheme for co-ordinates (x,y) of each WEC in an array.

Sparse PCE models of up to 15th order are constructed using Least Angle Regression (LARS) to identify the most influential basis terms while controlling model complexity. Surrogate accuracy is assessed using cross-validation error metrics.

2.6. Global Sensitivity Analysis

Variance-based global sensitivity analysis is performed directly on the PCE surrogate. First-order Sobol' indices are used to quantify the main effects of individual parameters on array power variability, while total-order indices capture the combined influence of main effects and interactions between wave parameters, PTO settings, and spatial configuration variables.

2.7. Scope and Limitations

The methodology is restricted to power-related performance metrics and relies on linear hydrodynamic assumptions. Nonlinear wave effects, advanced control strategies, and structural response metrics are not considered. Despite these limitations, the proposed framework is well suited for probabilistic performance assessment, sensitivity analysis, and preliminary design screening of WEC arrays and provides a scalable foundation for future array layout optimization studies.

3. RESULTS AND DISCUSSION

3.1. Surrogate Model Accuracy and Computational Efficiency

The surrogate model accuracy and computational efficiency are demonstrated in this paper in terms of quantitative error

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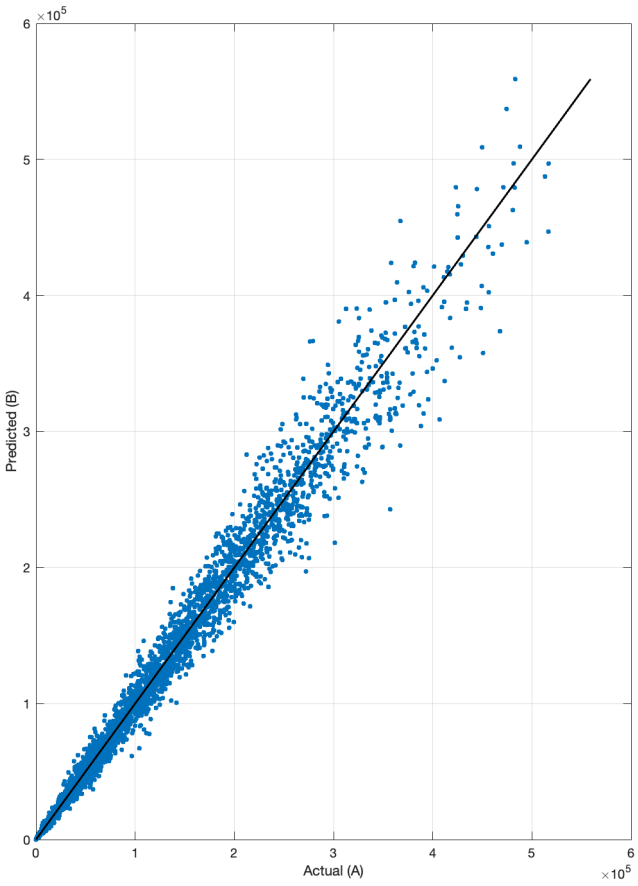

FIGURE 4: Parity plot of total power of an array between predicted (B) versus actual (A) values.

metrics, parity plot and computational cost comparison.

Quantitative error metrics: Leave-One-Out (LOO) error is used as a cross-validation error metric to assess surrogate accuracy. The LOO error for the surrogate presented in work was less than 0.003 that is an indicator of an excellent surrogate. This implies 99.7% of the variance is captured by the PCE surrogate and the surrogate has very strong predictive capability.

Parity plot: Figure 4 shows PCE-predicted total power vs. high-fidelity model where 'B' is predicted dataset and 'A' is actual dataset. In the parity plot R^2 is 0.983, Pearson corr(A,B) is 0.991 and Spearman ρ(A,B) is 0.998. The acceptable values of these parameters are larger than 0.95. All the parameters associated with parity plot are within acceptable range.

Computational cost comparison: Time per Capytaine–WEC-Sim evaluation is approximately 40 minutes versus time for a trained PCE evaluation for approximately 10^6 samples is 3 seconds. Therefore, the surrogate reproduces the high-fidelity model with low error while enabling orders-of-magnitude speedup.

3.2. Global Sensitivity Analysis Results

Sobol indices are sensitivity measures used in global sensitivity analysis to quantify the contribution of each input variable (or combinations of variables) to the output variance of a model. They help understand how uncertainties in input parameters affect the variability of the model output.

- **First-Order Sobol Indices** (S_i): The first-order Sobol index indicates the direct contribution of a single input variable to the output (Power generated by each device) variance. The first-order Sobol index quantifies the effect of varying a single input variable X_i on the output variance while keeping all other variables fixed. It is mathematically expressed as:

$$S_i = \frac{\mathrm{Var}[\mathbb{E}(Y \mid X_i)]}{\mathrm{Var}(Y)} \tag{1}$$

where, Y is the model output, X_i is the input variable of interest, $\mathrm{Var}(Y)$ is the total variance of the output, $\mathbb{E}(Y \mid X_i)$ is the expected value of Y given X_i.

Figure 5 shows the first-order Sobol index for 5a H_s and T_p, 5b PTO-damping coefficients and 5c X-coordinates of the devices (D1-7) in an array. It can be clearly seen that the wave parameters has the most influence on the power output, followed by PTO damping coefficients and the x-coordinates being the least influential. The influence of y-coordinates was negligible and therefor was excluded from the presented results.

- **Total Sobol Indices** (S_{Ti}): The total Sobol index captures all effects that include X_i, whether they are first-order effects or interactions with other variables. The total Sobol index accounts for both the main effect of a variable and all interaction effects involving that variable. It is expressed as:

$$S_{Ti} = 1 - \frac{\mathrm{Var}[\mathbb{E}(Y \mid X_{\sim i})]}{\mathrm{Var}(Y)} \tag{2}$$

where, $X_{\sim i}$ represents all input variables except X_i.

Figure 6 shows the first-order Sobol index for 6a H_s and T_p, 6b PTO-damping coefficients, 6c x-coordinates and 6d y-coordinates of the devices (D1-7) in an array. Similar to first-order Sobol index, the total Sobol index shows that the wave parameters has the most influence on the power output, followed by PTO damping coefficients and the x-coordinates being the least influential. Moreover, the spatial co-ordinates (x and y) show cross-contribution of the parameters (spatial parameters of devices in the array) in terms of total Sobol indices. No or negligible cross-interaction was observed between wave parameters and PTO damping of devices in an array.

Wave parameters (H_s and T_p) dominate overall variance, while PTO damping is the most influential controllable parameter. Spatial configuration contributes non-negligibly through interaction effects. However, the influence of spatial parameters are limited mainly to x-co-ordinates (distance in longitudinal direction). The y-coordinate of devices does not significantly contribute because the direction of waves is fixed (along the x-axis). The y-coordinate will start to contribute more when the

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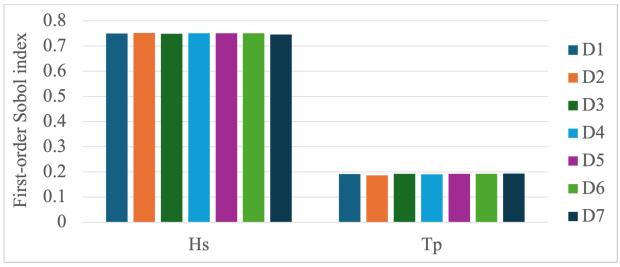
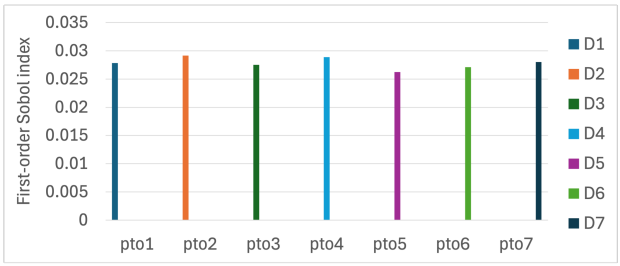
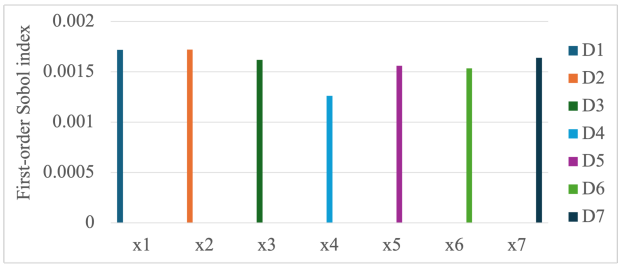


(a) H_s and T_p

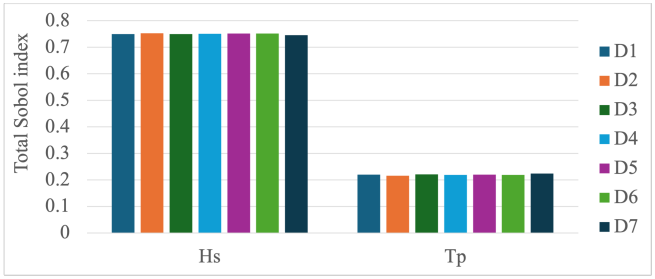


(b) PTO damping coefficients

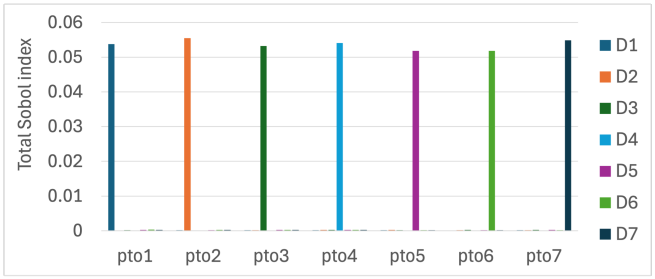


(c) x-coordinates

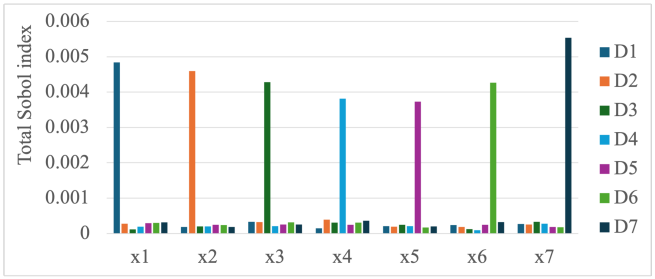
FIGURE 5: First-order Sobol indices for each of the 7 devices showing contribution of (a)H_s and T_p, (b)PTO damping coefficients and (c) x-coordinates



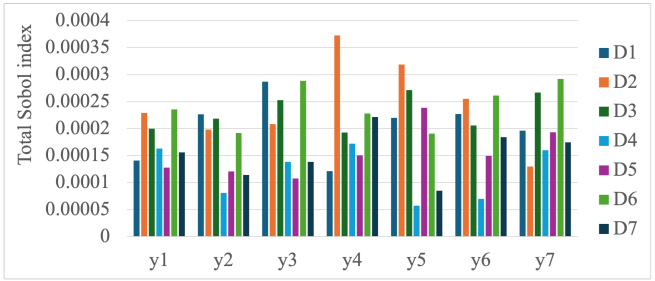
(a) H_s and T_p



(b) PTO damping coefficients



(c) x-coordinates



(d) y-coordinates

FIGURE 6: First-order Sobol indices for each of the 7 devices showing contribution of (a) H_s and T_p, (b) PTO damping coefficients, (c) x-coordinates and (d) y-coordinate

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wave directionality is also varied (will be included in future studies). The results will help future optimisation framework for chosing design space and weight for parametric influence.

3.3. Some preliminary results using PCE surrogate

Figure 7 shows the preliminary results using PCE surrogate to study the role of the wave parameters, PTO parameters and spatial parameters in consistent total power generation of 7 device arrays. The results clearly indicate that if the array design is not optimised for probabilistic sea state, the PTO parameter and spatial parameter optimisation will lead to sub-optimal results. These preliminary results form a strong basis for setting up an optimisation framework for arrays.

From the practical perspective Figure 7 demonstrates the need for designing reconfigurable PTO and spatial configurations adapted to the probabilistic sea state unlike the studies presented in literature where the spatial configuration and/ or PTO parameters were optimised for one or two specific sea states. It can be clearly seen in Figure 7 that no "specific" PTO or spatial parameters can lead to consistent power production across the multiple sea states. This is an important conclusion for designers to obtain optimum and consistent power production across multiple sea states throughout its operation period.

4. CONCLUSIONS

This study presents a robust surrogate modeling framework for the performance evaluation of wave energy converter (WEC) arrays, combining high-fidelity hydrodynamic simulations with polynomial chaos expansion (PCE)–based uncertainty quantification. By coupling frequency-domain hydrodynamic modeling with time-domain power estimation, the proposed approach enables efficient prediction of array power output across a broad range of sea states while significantly reducing computational cost relative to direct numerical simulations. The paper aims at showing the efficiency of the surrogate built that will be used in future works of optimisation and co-design frameworks. In current literature, mostly computationally expensive models exist which cannot run millions of combinations of probabilistic sea-state, spatial configuration and PTO parameters. The results demonstrate that the surrogate model accurately captures the dependence of array performance on key environmental parameters, with satisfactory validation metrics and controlled generalization error. Importantly, the framework overcomes limitations of previous studies that relied on fixed array configurations by providing a scalable and flexible tool suitable for array-level optimization, sensitivity analysis, and probabilistic performance assessment. Overall, the methodology offers a practical pathway toward improved design-space exploration and techno-economic evaluation of wave energy farms, supporting their integration into future offshore renewable energy systems.

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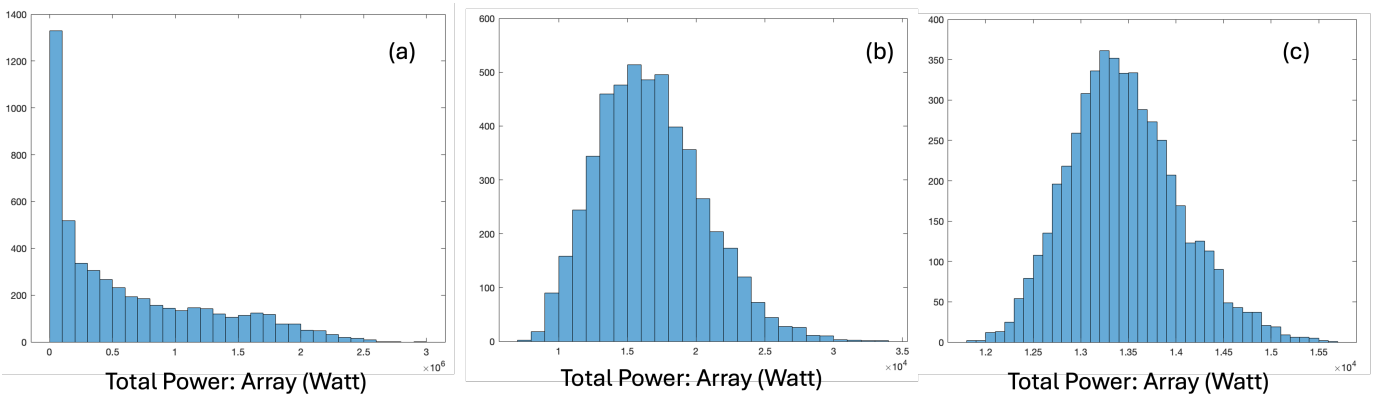

FIGURE 7: Histogram of total power generated by an array of 7 WECS with varying (a) wave parameters (H_S and T_p), PTO damping and coordinates; (b) PTO damping and coordinates; and (c) x-coordinates and y-coordinates .

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