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Collective prediction of power performance and fatigue loads in wave energy converters using a data-driven approach

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ABSTRACT

Due to the complexity of the ocean environment and wave energy converter (WEC) system, it has been an effort-demanding work to assess either the power performance or fatigue loads of WECs. This work attempts to apply a data-driven approach to increase the efficiency of the collective prediction of the power and fatigue load of a point-absorber type WEC. Nonlinear time-domain modeling is first established to estimate the power and fatigue loads, which is considered the reference data in this work. To demonstrate the performance of the applied data-driven approach, two prevalent power take-off (PTO) mechanisms are implemented to represent different characteristics of WECs. A data-driven approach, active learning Kriging (AK), is adapted to predict power and fatigue loads collectively, and a new learning function is defined to select the enriched wave cases for the active learning process. Results show that the applied active learning approach can accurately and simultaneously predict power and fatigue loads in both PTO mechanisms. Compared to pure numerical simulation, the proposed method only requires 15 simulations of sea state, and the computational effort is reduced by more than 20 times. The maximum prediction error is less than 2%. The data-driven approach could be a powerful tool for WEC system optimization, considering both power performance and fatigue loads.

1. Introduction

Ocean waves have vast potential for generating clean energy, and wave energy converters (WECs) are designed to harness electricity from ocean waves. This technology is expected to contribute significantly to the global energy transition. However, the commercialization of WECs lags far behind other renewable energy technologies like offshore wind turbines [1]. A major challenge in advancing WECs lies in their high levelized cost of energy (LCOE) [2]. To reduce the LCOE of WECs, the design process of WECs has to be performed properly and effectively. Despite numerous points to consider, two predominant indicators in the design process are power performance and load [3]. The power performance implies the production capacity, while the loads are inherently related to the reliability and durability of the designed WEC. Reasonable prediction of the power and loads could contribute to more reasonable designs which are expected to reduce the LCOE of WECs.

WECs absorb wave energy by interacting with incoming waves to move. In order to predict power performance, it is necessary to identify the dynamic behavior of WECs. The dynamic responses of WECs are highly dependent on the properties of waves, including wave heights and periods. As a result of the strong variability of ocean waves,

the power performance of WECs has to be estimated over a range of individual sea states to reveal the overall power performance. The variability of ocean waves has two implications in the performance evaluation of WECs. First, it is the long-term variability, which means the statistical characteristics of sea states are by no means constant. To describe the occurrence of numerous sea states of varied properties, the wave resource is normally characterized as a form of joint probability distribution of wave heights and periods based on long-term hind-cast statistics. Hence, to achieve a reasonable assessment, all the described sea states need to be addressed in the prediction of loads and power of WECs. The second implies the short-term variability, in which each sea state needs to be represented by irregular waves. To reflect the randomness of irregular waves, the predefined wave train, in numerical simulation, is supposed to cover a sufficient time duration and consist of a wide range of wave frequency components. As indicated in [4], the simulation duration is recommended to be at least 100 times the peak periods for properly simulating the WECs' responses in irregular waves. As a consequence of these two factors, significant time demands are commonly required to estimate the overall power performance and loads of WECs.

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Power performance identification of WECs has been widely performed and reported in a few recent studies [5–10], in which both numerical and experimental approaches have been adopted. Different types of WECs and different sea sites were considered in these studies. For instance, in [5], eight types of WECs in different principles were simulated by nonlinear time-domain models, and their power production was estimated for three different potential deployment sites. In [6], the wave-to-wire power performance of a newly designed WEC was evaluated by numerical modeling, in which the impact of power take-off sizing on the power performance of the WEC was investigated. Experimental tests were performed in [7,8] to estimate the power production of a floating point absorber WEC. [9] applied both numerical modeling and physical experiments to demonstrate the power performance of WECs in various wave conditions.

WECs must withstand complex and ever-changing environmental conditions during their designed lifespan. To ensure reliable designs, it is essential to accurately identify the loads these structures will face. The design loads for offshore structures are generally categorized into two types: extreme loading and fatigue loading. Fatigue loading primarily occurs during regular operation, resulting from cyclic stress variations over time, which accumulate strain and wear on the structure. In contrast, extreme loading represents the highest forces or loads the WEC may encounter during its lifetime, typically related to severe ocean conditions. Despite the significance of extreme loading estimation in WEC design, the current work is specifically focused on fatigue loading. This is simply because the fatigue loading examination of WECs is normally associated with the time-demanding estimation of loads under a large number of strongly variable operational conditions. Given the high-efficiency data-driven approaches, the application to fatigue estimation is inherently aligned to facilitate the acceleration of the design process of WECs. A few studies have carried out the fatigue load assessment for different WECs [11–16]. In [11], the loading on the mooring line of a floating WEC was estimated based on experimental tests. A realistic sea site was considered an environmental resource to further derive the cumulative fatigue based on the Palmgren–Miner rule and the rain-flow counting method. In [12], the fatigue analysis focused on the connection area between the PTO system and the WEC arm of the Wavestar concept. The impact of PTO control strategies on fatigue damage in the WEC was studied by implementing two different strategies. The fatigue loads of floating WEC mooring lines were assessed in [13], in which different simulation procedures were applied and compared. In [14,15], both experimental measurements and numerical prediction were used to estimate fatigue loads on mooring lines or at the PTO connection of floating WECs. In [16], numerical modeling was established to calculate the responses and induced loads on the hydraulic PTO system of a WEC, and the long-term fatigue loads were predicted by considering long-term wave resource data measured at the SEM-REV sea site.

The methods adopted in those studies mentioned above are either numerical, experimental approaches, or their combination. To obtain the overall power production and cumulative fatigue loads, the estimation must be performed for every sea state the WEC is expected to encounter. As explained in the text above, it is inevitably time- and effort-consuming to incorporate a variety of sea states in numerical models or experiments. To contribute to the design process of WECs, the primary motivation of the current research is to demonstrate the applicability of a data-driven approach in the absorbed power and fatigue load estimation of WECs. Data-driven approaches for power and fatigue load/damage prediction in offshore renewable energy have recently become increasingly popular. Many methods and applications [17–23] have been carried out. For instance, Golparvar et al. [17] and Ren et al. [18] used the Gaussian Process (Kriging) model for wind turbine power and wave converter power prediction. Ali et al. [19] applied cascaded feedforward neural networks for short-term wave power forecasting. Concerning fatigue load and damage prediction, Huchet et al. [21] and Ren and Xing [22,23] proposed an active

learning approach for offshore wind turbine fatigue estimation using the Kriging surrogate model. A review of the data-driven approach for wave energy applications can also be found in this work [24]. In the above works, only one critical performance character (power or fatigue) is considered in the data-driven approach. However, during the optimization process of the wave converter, both power performance and load fatigue need to be considered. In addition, among these approaches, compared to the classical data-driven approaches, active learning Kriging methods (adaptive/sequential sampling) demonstrate that they can make effective predictions both in power prediction [18] and fatigue load damage estimation [21,22]. Therefore, in this work, we adapt one active learning Kriging approach from the work of [22] for both WEC absorbed power and fatigue load prediction.

The rest of the paper is organized as follows: Section 2 presents the wave converter model and power and load estimation methods. Section 3 introduces a data-driven approach, the active learning Kriging (AK) method. Adaptations are made to the original approach for the collective prediction of power and fatigue load. In Section 4, the AK method is applied to power and fatigue load prediction considering one offshore site and two types of power take-off systems. In the end, conclusions and discussions are given in Section 5.

2. Load and power estimation of wave energy converters

2.1. WEC concept description

In this study, the utilized WEC concept refers to a floating heaving point absorber, depicted in Fig. 1. The WEC concept mainly comprises two main components. The first component is the floating buoy, and the second is the PTO system. The floating buoy is simplified as a sphere, and the radius R is defined as 2.5 m. The draft of the buoy is set to be 2.5 m as well, assuming its mass is equal to that of displaced water. Excited by incoming waves, the floating buoy oscillates, which results in relative motion between the buoy and the PTO system. The PTO system then uses relative motion for electricity generation. As a core component, the PTO system plays a significant role in the dynamic responses and power performance of WECs. As indicated by various studies, a variety of PTO mechanisms with different operating principles, sizes, and efficiencies have been applied in wave energy conversion [5,25,26]. Two predominant PTO types are implemented in this work to comprehensively verify the applicability of the proposed method to different PTO systems. They are the linear PTO system and hydraulic PTO system, respectively, which will be detailed in the following text.

2.2. Wave resource of the deployment site

The power performance and loads of the WEC are strongly related to environmental inputs. Despite the inevitable effects of tides and wind, the most relevant input to WECs can be expected to be ocean waves. In this sense, ocean waves are considered the only type of environmental input in the load and power performance identification. A 30-year hind-cast wave data generated by the high-resolution spectral wave model for a site at the North Sea, specifically near the Wadden Sea region in the Netherlands, is used as the environmental input to the load and performance estimation of the WEC [27]. The spectral wave data covers the wave resource information from 1992 to 2021, with an interval of half an hour. The data points are shown in Fig. 2(a). To better represent the wave resource, the data points are processed as a form of the joint probability distribution of the significant wave height and peak period, usually known as scatter diagrams. The scatter diagram depicts the probability of occurrence of each sea state for the sea site, which is given in Fig. 2(b).

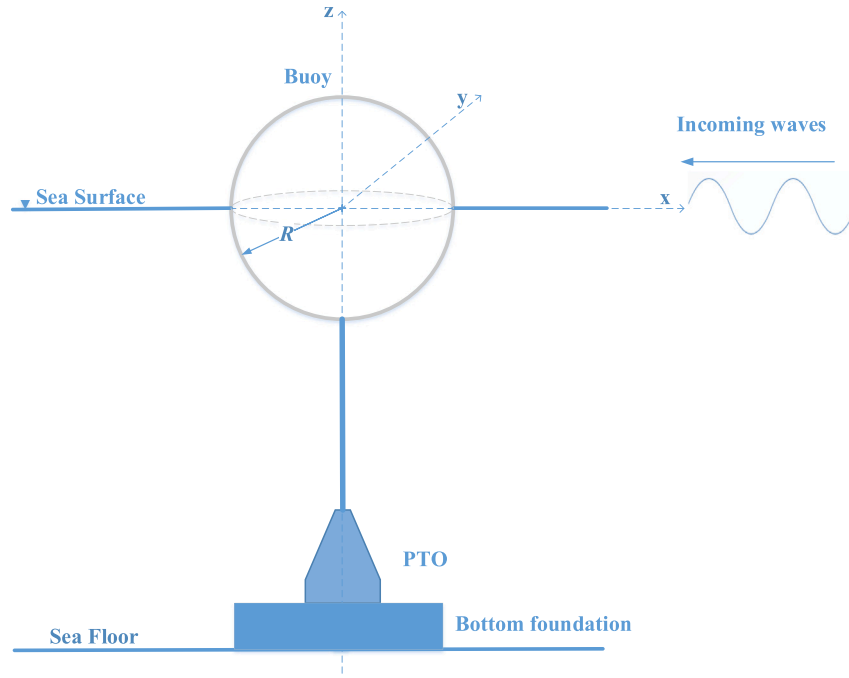


Fig. 1. Schematic of the spherical heaving point absorber with a bottom founded PTO system.

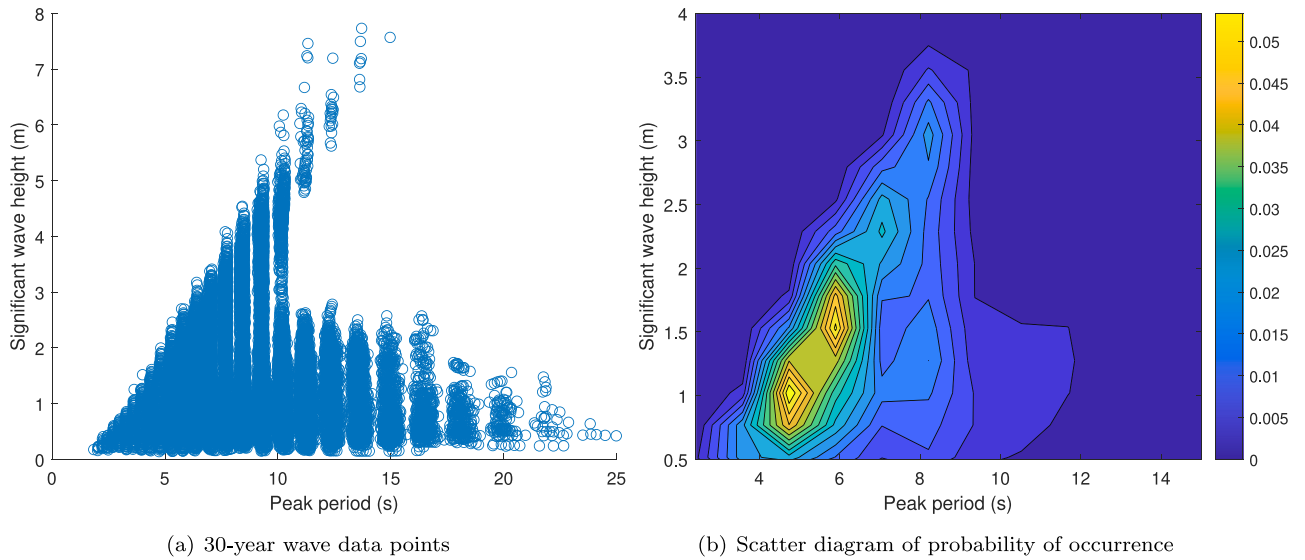


Fig. 2. Wave resource characterization.

2.3. Numerical modeling

To estimate the power and loads of the WEC, a nonlinear time-domain model is established based on the open-source software WEC-sim [4,28]. WEC-Sim has been widely verified and validated in a series of previous work [29–32], which supports the credibility of the numerical model adopted here for power and fatigue estimation. The equation of motion of the WEC is formulated based on the Cummins equation [33]:

$$(M + M_r(\infty))\ddot{z}(t) = F_e(t) + F_{pto}(t) + F_{hs}(t) + F_{es}(t) + \int_0^t K_{rad}(t - \tau)\dot{z}(\tau)d\tau \quad (1)$$

where M and M_r are the mass of the WEC and the added mass, respectively; z , $\dot{z}$ and $\ddot{z}$ stand for the displacement, velocity, and acceleration of the buoy; t indicates the time; F_e , F_{pto} , F_{hs} and F_{es} are the excitation force, PTO reaction force, hydrostatic force and end-stop force respectively; the convolution term on the right hand of the equation represents the radiation force, and K_{rad} is the radiation impulse function. To reduce the computational load, the convolution term is approximated by a state-space representation in the numerical integration of WEC-sim [4]. The hydrodynamic coefficients, including excitation force coefficients, added mass, and radiation impulse function, are derived based on the open-source boundary element method solver Nemoh [34]. The hydrostatic force of WEC is calculated as:

$$F_{hs} = -K_{hs}z(t) \quad (2)$$

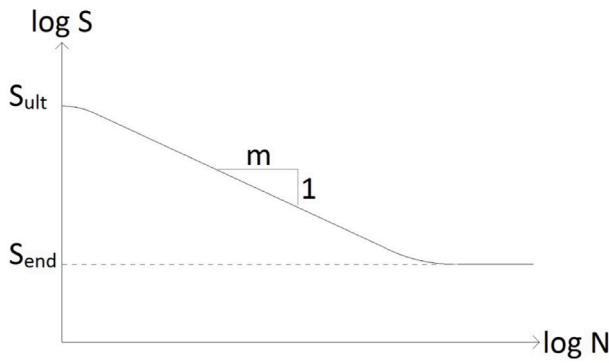


Fig. 3. Schematic of an S-N curve.

where K_{hs} stands for the hydrostatic stiffness. The end-stop mechanism acts as a spring located at the two sides of the stroke of the floater or the moving part of the PTO system, and the end-stop force is given as

$$F_{es}(z) = \begin{cases} -K_{es}(z + Z_{es}), & z \leq -Z_{es} \\ 0, & |z| < Z_{es} \\ -K_{es}(z - Z_{es}), & z \geq Z_{es} \end{cases} \quad (3)$$

where K_{es} and Z_{es} represent the end-stop spring stiffness and the stroke limit where the end-stop mechanism begins to take effect. In this study, K_{es} is set to be 200 kN/m and Z_{es} is set to be 1.25 m. It is acknowledged that the variation of these parameters would inevitably affect the load and response of the WEC. Nevertheless, the purpose of the current work is to identify the influence of PTO parameters on load estimation. Thus, it is fair to maintain the consistency of the end-stop parameters throughout the simulations. For the sake of higher simulation accuracy, the nonlinear Froude–Krylov force and nonlinear restoring force are considered in the numerical model using a re-meshing routine method. This is realized by an advanced feature, that is, the “NonlinearHydro” function, embodied in WEC-sim [28]. These two force components are recalculated at each time step based on the instantaneous wetted surface of the WEC and the instant wave elevation. In addition, a quadratic term is included to represent the viscous drag effect on the dynamic responses of the WEC, and the drag coefficient is set as 0.6, referring to the investigation shown in [35]. In addition, the Jonswap spectrum is utilized in the simulations to describe the irregular waves. Once the time-dependent dynamic responses of the WEC are obtained by solving (1), the power and the load can be derived. The time-averaged absorbed power of the WEC at each sea state can be calculated as

$$P = \frac{\int_0^{T_{sim}} F_{pto}(t) \dot{z}(t) dt}{T_{sim}} \quad (4)$$

where T_{sim} means the simulation duration for each case.

In this WEC concept, the PTO system is connected to WEC only by a rigid rod. The rod is subjected to a large number of cyclic loads in the oscillatory movement of the WEC. Hence, it is important to examine the fatigue load on the connection rod of the PTO system. The load exerted on the PTO rod is equivalent to the derived PTO force F_{pto} . Fatigue failure of structural components is predominantly evaluated by an empirical approach, namely $S-N$ curve. An example of the $S-N$ curve is illustrated in Fig. 3. Basically, the $S-N$ curve demonstrates the number of loading cycles N to failure at a constant load amplitude S . The slope of $S-N$ curve m is usually obtained empirically and varies with the material. In this work, the curve slope m is selected to be 6, assuming that the PTO rod is manufactured of cast iron [36].

As the PTO force is strongly variable throughout the operational life of WECs, the Palmgren–Miner rule is adopted here to estimate the cumulative damage of each loading cycle. The Palmgren–Miner rule operates on the premise that the cumulative damage from each load

cycle does not depend on the order in which the cycles happen. In this study, the equivalent damage load is adopted to represent the level of cumulative fatigue damage on the PTO rod. As demonstrated in [36], the total damage equivalent load, F_{eq} , can be derived as

$$F_{eq} = \left(\sum \frac{F_i^m n_i}{N_{eq}} \right)^{\frac{1}{m}} \quad (5)$$

where i stands for the load range i_{th} bin, F_i represents the load amplitude of the corresponding bin, and the number of cycles within that load range is given as n_i . F_i and n_i can be calculated using the rain-flow counting method [37]. For each sea state, the time histories of the PTO force obtained by the numerical model are used to generate an equivalent PTO load by (5). As the simulation duration of each sea state is one hour, the one-hour equivalent PTO load $F_{pto,1hr}$ corresponding to the sea state can be calculated by (5). The cycle number N_{eq} in (5) is approximated as the hourly average cycle number throughout the entire range of probable sea states showing on the scatter diagram, which can be derived as

$$N_{eq} = \sum \rho(H_s, T_p) \frac{3600}{T_{avg}(H_s, T_p)} \quad (6)$$

where $\rho(H_s, T_p)$ represents the probability of occurrence of each sea state; T_{avg} stands for the average period, which is transferred from T_p by multiplying a factor of 0.777 given the Jonswap spectrum [38]. It is noted that N_{eq} is a constant number depending on the characteristics of the wave resource at the sea site.

2.4. Linear PTO system

The linear PTO system can be simplified as a passive damper, which can be expressed as

$$F_{pto}(t) = -B_{pto} \dot{z}(t) \quad (7)$$

where B_{pto} is the PTO damping, and it can be varied for different sea states. As demonstrated in [10,39], based on a linear representation of WECs, the optimal PTO damping maximizing the power absorption can be derived as

$$B_{pto,opt}(\omega) = \sqrt{B_{rad}(\omega)^2 + X_i(\omega)^2} \quad (8)$$

where $B_{pto,opt}(\omega)$ is the optimal PTO damping at the specified wave frequency ω ; B_r and X_i are the frequency-dependent coefficients, namely radiation damping and intrinsic reactance. The radiation damping is numerically calculated by Nemoh, and the intrinsic reactance is expressed as

$$X_i(\omega) = \omega[M + M_r(\omega)] - \frac{K_{hs}}{\omega} \quad (9)$$

It is noted that the derived optimal PTO damping $B_{pto,opt}$ is frequency-dependent, which implies the applicability of this method is originally limited to regular wave conditions. To suit the irregular sea states, the energy period T_e is used corresponding to the wave period in regular waves. In addition, the derived optimal PTO damping normally applies to the operational regions of WECs, in which nonlinear effects are negligible. In this sense, the derived PTO damping is not necessarily optimal for power production. Nevertheless, it is thought to be fair since the focus of the current paper is to investigate the applicability of the proposed data-driven method to the WECs.

2.5. Hydraulic PTO system

Hydraulic PTO systems are also commonly applied in wave energy conversion. Hydraulic PTO systems can be modeled as Coulomb damping [5], expressed as

$$F_{pto}(t) = -\text{sgn}(\dot{z}) C_{pto} \quad (10)$$

where C_{pto} is the PTO force coefficient which is a constant in each sea state but can be adjusted to different sea states. To avoid infinite derivatives of the mathematical expression around regions $|\dot{z}| = 0$, a slope

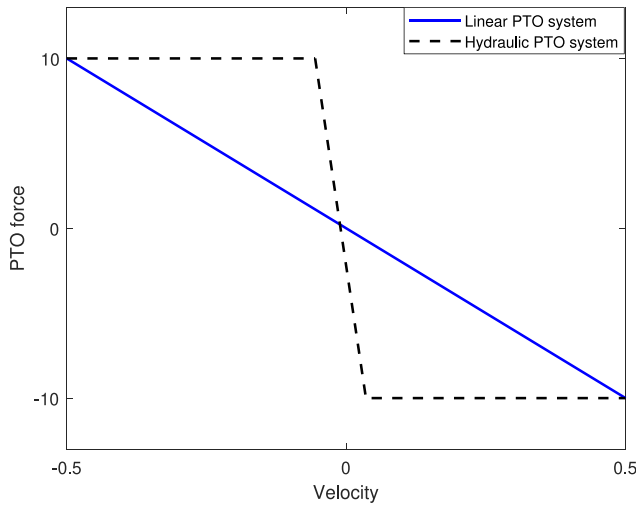


Fig. 4. Illustration of hydraulic PTO force.

function is added in the range to facilitate numerical implementation, as illustrated in Fig. 4.

Due to nonlinear characteristics, the determination of the optimal PTO force coefficient of hydraulic PTO systems is not as straightforward as that in the linear PTO system even in regular sea states. The maximum-search algorithm was commonly applied in previous studies to find the optimal coefficient for power performance. However, the purpose of this work is not to explore the potential of the WEC performance. Instead, by taking into account the hydraulic PTO system, it is intended to verify the applicability of the proposed method to the variation of the PTO behaviors. The large time demands of the maximum search are not expected to significantly improve the work's main contribution. In this sense, a simplified approach is implemented to determine the PTO force coefficient. Specifically, with the obtained PTO damping for linear PTO systems, equaling the root mean square (RMS) value of the PTO force of the hydraulic PTO system and that of the linear PTO system within a wave period of a regular sea state gives

$$\text{RMS}\left(\int_0^{\frac{2\pi}{T_e}} C_{pto}(T_e)\right) = \text{RMS}\left(\int_0^{\frac{2\pi}{T_e}} -B_{pto}(T_e)\dot{z}(t)\right) \quad (11)$$

Before running the nonlinear model for irregular waves, $\dot{z}(t)$ in (11) is calculated first in each sea state with a fully linear model for a regular wave. This is intended to obtain the PTO parameters efficiently. Then, the PTO force coefficient C_{pto} can be easily derived for each simulation case.

3. Data-driven approaches

In recent years, many data-driven approaches have been used to offshore renewable power and fatigue load predictions. These methods can be roughly classified into “one-shot” and “active learning” approaches. The one-shot approach uses a well-trained machine-learning model for prediction, but it requires a lot of data for a well-trained model. Compared to the one-shot approach, the active learning (adaptive/sequential sampling) approach uses fewer datasets and makes a more accurate prediction, which has attracted more and more attention [40–43]. A general workflow of active learning approaches is given in Fig. 5. As shown in the figure, the surrogate model, learning function, and stopping conditions are critical for prediction efficiency and accuracy in the active learning data-driven approaches.

3.1. An active learning kriging approach

In this work, the Kriging surrogate model is used for both power and fatigue damage prediction. The Kriging surrogate model is well-suited for nonlinear response prediction and provides inherent uncertainty measures over the projections to assist the active learning iterations. The Kriging model was conceptualized by Krige [44] and subsequently refined by Matheron [45]. One active learning algorithm, first proposed by Ren and Xing [22] for the fatigue assessment of offshore wind turbine structures, is adapted for both power and fatigue load estimation. The Kriging model prediction ($\hat{y}$) is applied to assess the average absorbed power and equivalent fatigue load under different sea states. The annual average absorbed power and equivalent fatigue load can be formulated as follows:

$$\hat{Y} = \sum_{i=1}^{N_{ss}} \hat{y}_i \rho_i \quad (12)$$

where y_i is the predicted absorbed power or equivalent fatigue load of the i th sea state, ρ_i is the related probability of occurrence, and N_{ss} is the total number of sea states. The active learning Kriging approach [22] considers the prediction error of the Kriging model, and its predicted upper and lower bounds of absorbed power or fatigue load can be expressed:

$$\hat{Y}^u = \sum_{i=1}^{N_{ss}} \hat{y}_i^u \rho_i \quad \text{and} \quad \hat{Y}^l = \sum_{i=1}^{N_{ss}} \hat{y}_i^l \rho_i \quad (13)$$

where $\hat{y}_i^u$ and $\hat{y}_i^l$ are, respectively, the predicted upper and lower bound prediction in i th sea state. They can be calculated as follows:

$$\hat{y}_i^u = \hat{y}_i + \lambda \sigma_{\hat{y}_i} \quad \text{and} \quad \hat{y}_i^l = \hat{y}_i - \lambda \sigma_{\hat{y}_i} \quad (14)$$

where $\lambda \approx 1.96$ is set for the 95% confidence interval and $\sigma_{\hat{y}_i}$ is the predicted error of the Kriging model at i th sea state. The difference between the predicted value and its upper(lower) bound can then be formulated like:

$$e_{\hat{Y}} = \hat{Y}^u - \hat{Y} = \hat{Y} - \hat{Y}^l = \lambda \sum_{i=1}^{N_{ss}} \sigma_{\hat{y}_i} \rho_i = \lambda \sum_{i=1}^{N_{ss}} E P_i \quad (15)$$

where $E P_i$ is the defined learning function that focuses on the Kriging prediction error ($\sigma_{\hat{y}_i}$) and wave probabilities of occurrences (ρ_i). The active learning process is to search the i^* th sea state with the maximum value of $E P_i$, which gives:

$$i^* = \arg \max(E P_i) \quad \text{where } i = 1, 2 \dots N_{ss} \quad (16)$$

The active learning process will ensure the Kriging prediction accuracy at high probabilities of occurrences. Also, it can efficiently reduce the difference $e_{\hat{Y}}$ as the Kriging surrogate model is an exact interpolator. The active learning process will stop when:

$$\delta = \frac{e_{\hat{Y}}}{\hat{Y}} \leq \epsilon \quad (17)$$

where δ represents the ratio between the error and the predicted value, and ϵ is the threshold value of the convergence criterion, which equals 0.1 as recommended in the original work. The original approach only focuses on a single output. However, the absorbed power and fatigue load are both critical for the wave converter during the design optimization process.

3.2. Adapt the active learning approach to multi-output prediction

This sub-subsection proposes an approach based on the previous work for the multi-output prediction approach. The proposed approach aims to simultaneously predict the multi-output values with less computational cost. In the proposed approach, Kriging models ($\hat{y}^k$) are used to predict the equivalent fatigue load or absorbed power under various

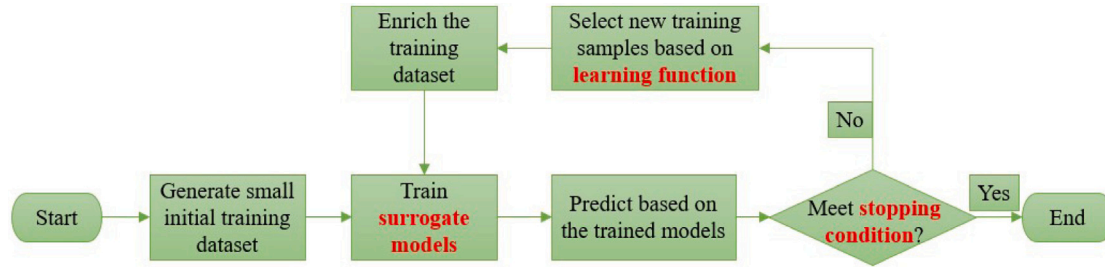


Fig. 5. General workflow of active learning data-driven approaches.

sea states. The annual average value of the k th output in the wave energy converter is given:

$$\hat{Y}^k = \sum_{i=1}^{N_{ss}} \hat{y}_i^k \rho_i \quad (18)$$

where $\hat{y}_i^k$ denotes the predicted value of the k th output (power or fatigue load) under the i th sea state. Consequently, the error between the predicted value and its upper (lower) bound can be expressed as follows:

$$e_{\hat{Y}}^k = \lambda \sum_{i=1}^{N_{ss}} \sigma_{\hat{y}_i}^k \rho_i = \lambda \sum_{i=1}^{N_{ss}} EP_i^k \quad (19)$$

The error ratio (δ^k) in the k th output value can be given:

$$\delta^k = \frac{e_{\hat{Y}}^k}{\hat{Y}^k} \quad (20)$$

The convergence criterion of the proposed data-driven approach is to ensure that the error ratio at each output will be less than the threshold value ϵ :

$$\max(\delta^k) \leq \epsilon \quad \text{where } k = 1, 2 \dots M_{mo} \quad (21)$$

where M_{mo} is the total number of outputs considered in the wave converter devices. In this case, $M_{mo} = 2$ is considered as there are only two outputs (absorbed power and equivalent fatigue loads). If the stopping condition is not satisfied ($\max(\delta^k) > \epsilon$), this means the Kriging models still need to be updated. Unlike the original approach, the new learning function focuses not on a single output but multiple outputs. Therefore, a new learning function is defined to consider the multi-outputs, which gives:

$$MEPn_i = \sum_{k=1}^{M_{mo}} EPn_i^k \quad (22)$$

where EPn_i^k is the normalized value of EP_i^k , as the proposed approach considers each output equally important. Therefore, the EP_i^k values are normalized by the maximum value of EP_i^k , which gives:

$$EPn_i^k = \frac{EP_i^k}{\max(EP_i^k)} \quad (23)$$

The active learning process of the proposed approach then aims to search the i^* th sea state with the maximum value of $MEPn_i$, and it can efficiently reduce the predicted error of multi-outputs, which gives:

$$i^* = \arg \max(MEPn_i) \quad \text{where } i = 1, 2 \dots N_{ss} \quad (24)$$

The general workflow of the proposed approach is given in Fig. 6. Initially, a few (N_{DoE}) sea states are selected, and the related simulated values are used to train Kriging models. In this work, there are M_{mo} ($M_{mo} = 2$) Kriging models for the training process, as there are two critical factors: absorbed power and equivalent fatigue load. The defined learning function will select the new enriched sea state and update the Kriging models when the stopping condition is not met.

4. Results and discussion

In this part, the proposed method is applied to predict the annual average absorbed power and equivalent fatigue load. The two case studies consider an offshore site in the North Sea with 30-year hind-cast wave sources. Table 1 presents the design domain of the point absorber WEC and the initial sea states for training Kriging models. The significant wave height (H_s) is from 0.262 m to 4.061 m with an interval of 0.253 m. The peak period (T_p) starts from 2.421 s to 24.409 s with an interval of 1.157 s. In total, 320 different sea states are considered for annual average power and equivalent fatigue load estimation. For each sea state, a total of 1-hour time-domain simulation is carried out to derive average absorbed power and equivalent fatigue load, as shown in Figs. 7 and 8. Fig. 7 illustrates the instantaneous power and PTO load of the WEC with a linear PTO system, while Fig. 8 presents the simulated results of the WEC with a hydraulic PTO system. It is noted that the PTO force profiles of the two PTO systems are clearly different. This is because the hydraulic PTO system is modeled as Coulomb damping, but the linear PTO system is represented as a linear damper. As for initial sea states for training Kriging models, they are selected by grid sampling based on the design domain of H_s and T_p . $N_{DoE} = 12$ sea states are initially used to train the Kriging models. In addition, two typical power take-off systems, namely linear and hydraulic, are tested to demonstrate the performance of the proposed data-driven approach.

4.1. WEC with a linear PTO system

The point absorber WEC with a linear PTO system is investigated in the first case. With the simulation results at all the sea states obtained, the time-averaged power and equivalent PTO fatigue load can be derived based on Eqs. (4) and (5), which are depicted in Fig. 9. Fig. 9(a) presents the time-averaged absorbed power in an 1-hour simulation period under different sea states while Fig. 9(b) presents the equivalent fatigue load of an 1-hour simulation period at the PTO component. The product values of absorbed power and the wave probability of occurrences are given Fig. 10(a), and the product values of equivalent fatigue loads and probability of occurrences are presented Fig. 11(a).

The proposed method is here applied to predict annual average absorbed power and equivalent fatigue load. First, the initial sea states are simulated, and the results are used to train the Kriging models. There are two Kriging models: one is for the absorbed power, and the other is for equivalent fatigue loads. The initial prediction of AP and EFLs are depicted in Figs. 10(b) and 11(b) and the blue points are the initial sea states for training Kriging models. Compared to the true (simulated) values in Figs. 10(a) and 11(a), the initial predictions are much different in overall distribution and amplitude. The annual average values of initial predictions are inaccurate, and the stopping condition is not satisfied, as shown in Fig. 12. Then, the active learning process starts to select the new sea state to update the Kriging models. The first enriched case is plotted in Figs. 10(c) and 11(c), and the red star point represents the enriched sea states. The prediction values with the 1st enriched case get closer to the simulated ones, and the

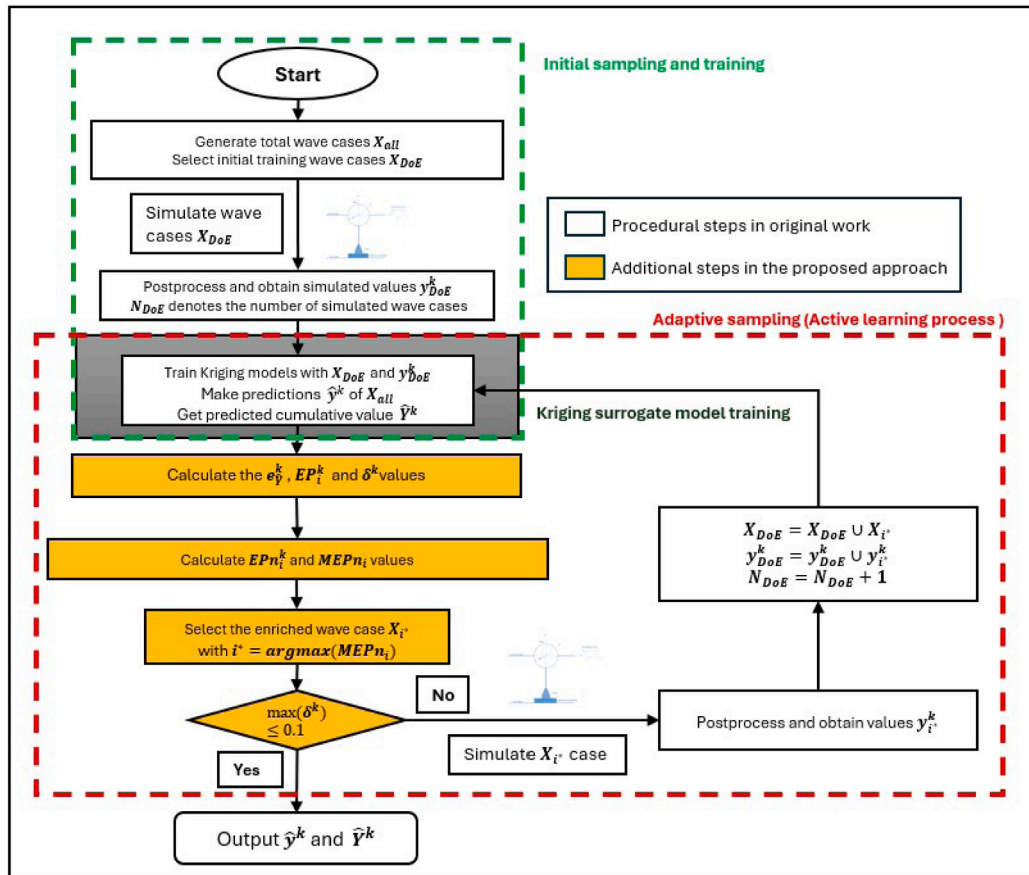


Fig. 6. General workflow of the proposed active learning Kriging approach.

Table 1

Sea states for numerical analysis and initial Kriging model training.

Parameter	Design domain	Discretization	Number of cases	Initial grid samples
H_s (m)	[0.262, 4.061]	0.253	16	[0.262, 2.035, 4.061]
T_p (s)	[2.421, 24.409]	1.157	20	[2.421, 9.364, 16.308, 23.251]
Total cases			$N_{total} = 320$	$N_{DoE} = 12$

prediction accuracy of annual average values is also significantly improved, as shown in Fig. 12(a) and (b). This means the defined learning function can effectively select the “useful” sea state case to improve the prediction accuracy. The active learning process will continue to select the new sea states to update the Kriging models until the predefined convergence condition is met. In the end, only three enriched sea states are needed, and the final prediction values are depicted in Figs. 10(d) and 11(d). The three sea states are primarily located in the area that contributes significantly to the annual average values. In addition, compared to simulated values, the final prediction can predict both overall distribution and amplitude well. The yearly average values will also approach the simulated values in the end, as depicted in Fig. 12(a) and (b). The related δ^k values are less than 0.1 as depicted in Fig. 12(c).

The results of simulated and predicted values are summarized in Table 2. In total, the proposed method only requests 15 simulated cases, including initial cases and enriched cases. Compared to 320 cases for the pure numerical analysis, the computational efficiency has increased more than 21 times. Here, the increased computational efficiency is calculated based on the ratio of simulated wave cases between the

pure numerical method and the proposed method. More importantly, regarding the prediction accuracy of yearly average values, the maximum difference between simulated values and predicted values is less than 2%. The proposed method can effectively predict the absorbed power and equivalent fatigue load with accuracy and at much less computational cost.

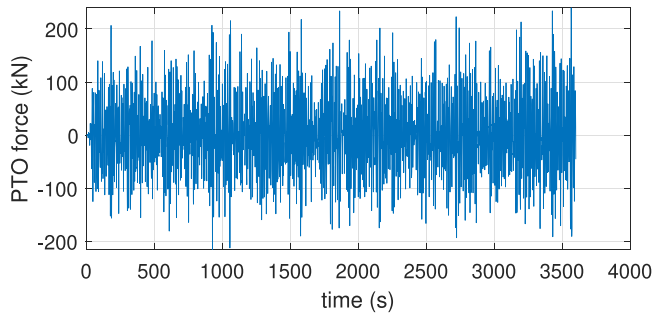
4.2. WEC with a hydraulic PTO system

In this part, the WEC with a hydraulic PTO system is also tested using the proposed data-driven method. The hydraulic PTO system is another type of PTO system that dominates WECs. Like the previous case study, 320 numerical simulations are used as references. The simulated absorbed power and equivalent fatigue load under different sea states are derived and shown in Fig. 13. The related product values with wave probability of occurrences are, respectively, given in Figs. 14(a) and 15(a).

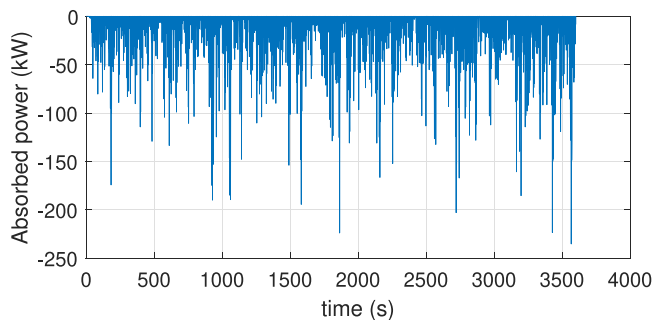
The proposed method is applied to predict the annual average values of the absorbed power and equivalent fatigue load. $N_{DoE} = 12$

Table 2
Prediction results with the linear PTO system.

Method	Linear PTO	Simulated cases	Annual average value	Error (%)	Increased efficiency (times)
Numerical analysis	Absorbed power (W)	320	9266.65	–	≈ 21
	Equivalent fatigued load (N)		103 849.47		
Proposed AK method	Absorbed power (W)	15	9305.77	0.42	
	Equivalent fatigued load (N)		101 824.09	1.95	



(a) Instantaneous PTO load versus time



(b) Instantaneous absorbed power versus time

Fig. 7. Simulation results of the WEC with a linear PTO system, $H_s = 2.54$ m, $T_p = 10.52$ s.

initial sea states are simulated and used to train the Kriging models. The initial predictions are much different than the simulated values, as shown in Figs. 14(b) and 15(b). The initial predicted average values also have a big difference from the simulated values, as demonstrated in Fig. 16(a) and (b). The convergence condition also does not satisfy. The active learning starts to select the new sea state to update the Kriging models. With the first enriched case, the prediction will get much better than the initial prediction, as shown in Figs. 14(c) and 15(c). The newly selected case also significantly improves the prediction accuracy of the annual average values, as shown in Fig. 16. The active learning process will continually select new cases and update Kriging models until the stopping condition is met. Like the previous case, only three sea states are needed at the end, and the enriched three cases are the same sea state as the previous case. This is because the proposed method aims to predict the annual average absorbed power and equivalent fatigue load. The wave probability of occurrences will play a significant factor, as shown in Eq. (12), and the same offshore site is considered in both case studies. Therefore, the enriched cases are likely the same. The final prediction, as depicted in Figs. 14(d) and 15(d), is much closer to the simulated values in Figs. 14(a) and 15(a). The final prediction values can capture the distribution of AP and EFLs well. The final predicted average values in Fig. 16(a) and (b) are also nearly the same as the

simulated ones. The δ^k values, as shown in Fig. 16(c), are less than 0.1. The results of the simulated values and final prediction values are summarized in Table 3. Like the previous, the computational efficiency is increased more than 21 times, and the maximum difference is less than 1%. Even considering different PTO systems, the proposed data-driven method can also effectively predict the annual average absorbed power and equivalent fatigue load without compromising accuracy.

5. Conclusions and perspectives

This work adapts a data-driven approach to predict a point-absorber wave energy converter's annual average absorbed power and equivalent fatigue load. The case studies use an offshore site in the North Sea with 30-year hind-cast wave resources. Also, two prevalent power take-off mechanisms, namely linear and hydraulic PTO systems, are considered for the case studies. A data-driven approach, named the active learning Kriging approach, was originally designed for offshore wind turbine fatigue estimation. It is adapted in this work for both absorbed power and equivalent fatigue load prediction. A new learning function is defined to select the sea state to reduce both prediction errors in absorbed power and fatigue load during the active learning process. Results demonstrate that:

The proposed method can simultaneously and effectively estimate the absorbed power and equivalent fatigue load. The initial prediction values may differ from the actual values, as only a limited number of sea states are considered. However, with the active learning process, the prediction values can quickly approach the true values. The proposed new learning function can efficiently select enriched sea states that contribute most to the annual average absorbed power and equivalent fatigue load values. Also, it is noted that the enriched cases are affected by the wave probability of occurrences at the offshore site. Due to the same offshore site in both cases, the three enriched cases are the same. In both PTO systems, only 15 sea states are needed to predict both absorbed power and equivalent fatigue load accurately. The computational efficiency is increased by more than 20 times compared to the pure numerical simulations. The maximum error between predicted and simulated values is less than 2%. The proposed approach could serve as a useful tool for wave energy converter optimization, considering both absorbed power and fatigue load.

However, it is noted that the proposed method relies on numerical simulations without experimental validation in this study. One of the future research areas followed up by the current work is to integrate the experimental data obtained by wave tank testing into the proposed methodology framework. The experimental results could first be used as a validation reference to numerical results derived via WEC-Sim, enhancing the credibility of the numerical model, particularly for high-wave conditions where the nonlinearity of hydrodynamic behavior is intensified and further affects the estimation accuracy of dynamics and loads of the PTO system. Additionally, the sensitivity of the active learning process to the initial training samples is not investigated. A better initial sample selection could also further enhance the computational efficiency of the proposed method. Also, the focus is mainly on a single WEC type and an offshore site. Other WEC types and sea sites with varied characteristics of wave resource would also require further investigation to demonstrate the robustness of the proposed

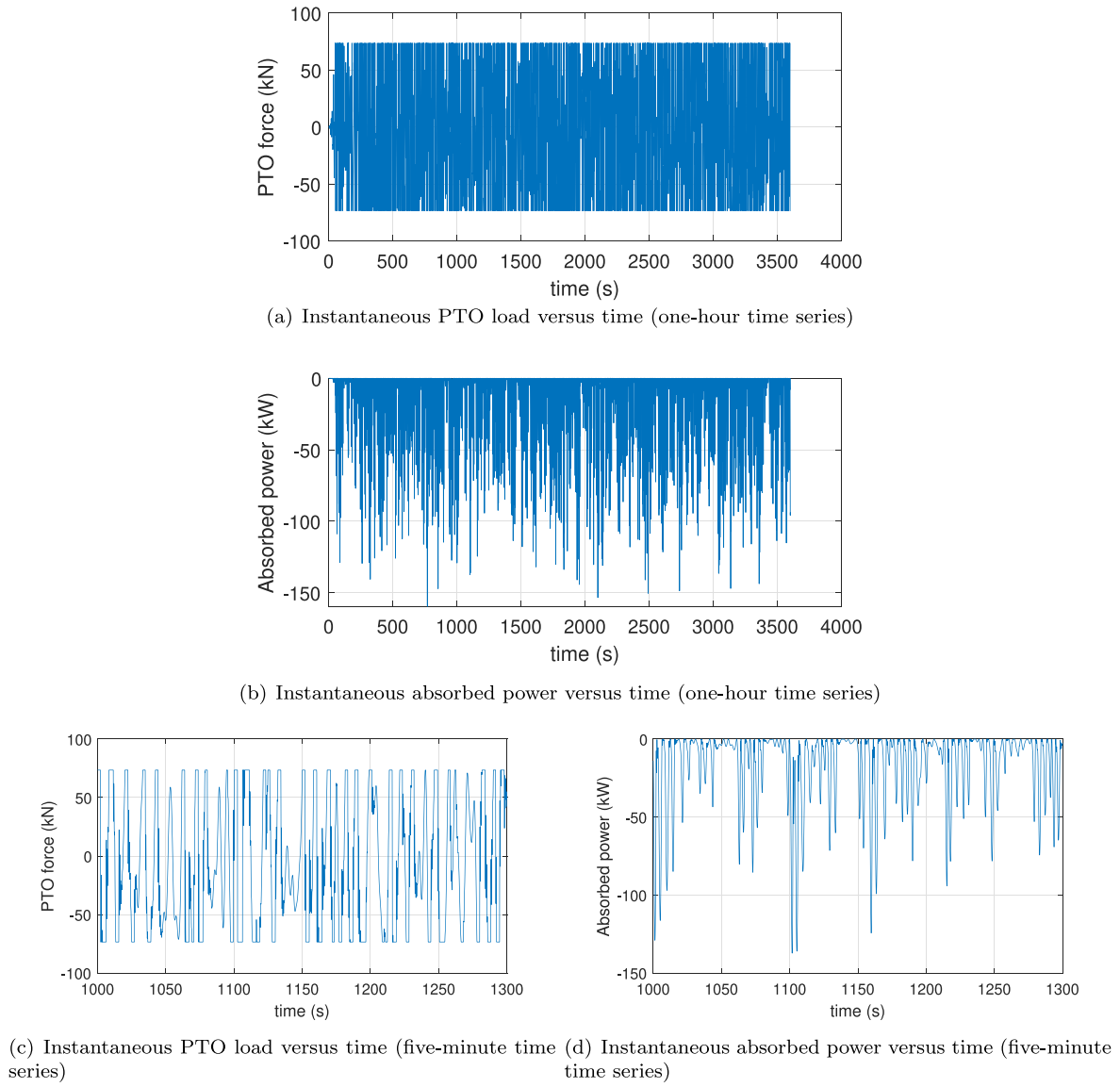


Fig. 8. Simulation results of the WEC with a hydraulic PTO system, $H_s = 2.54$ m, $T_p = 10.52$ s.

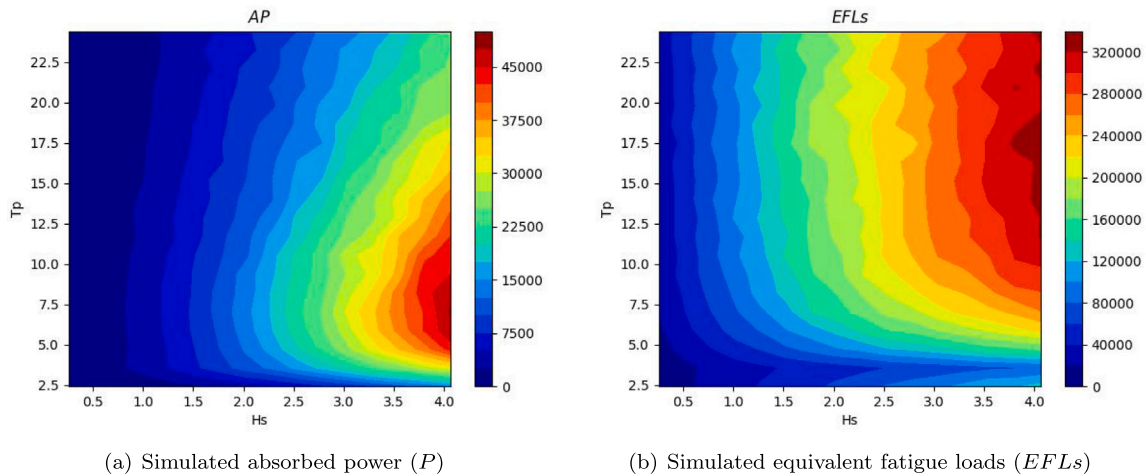


Fig. 9. Simulated results with linear PTO system.

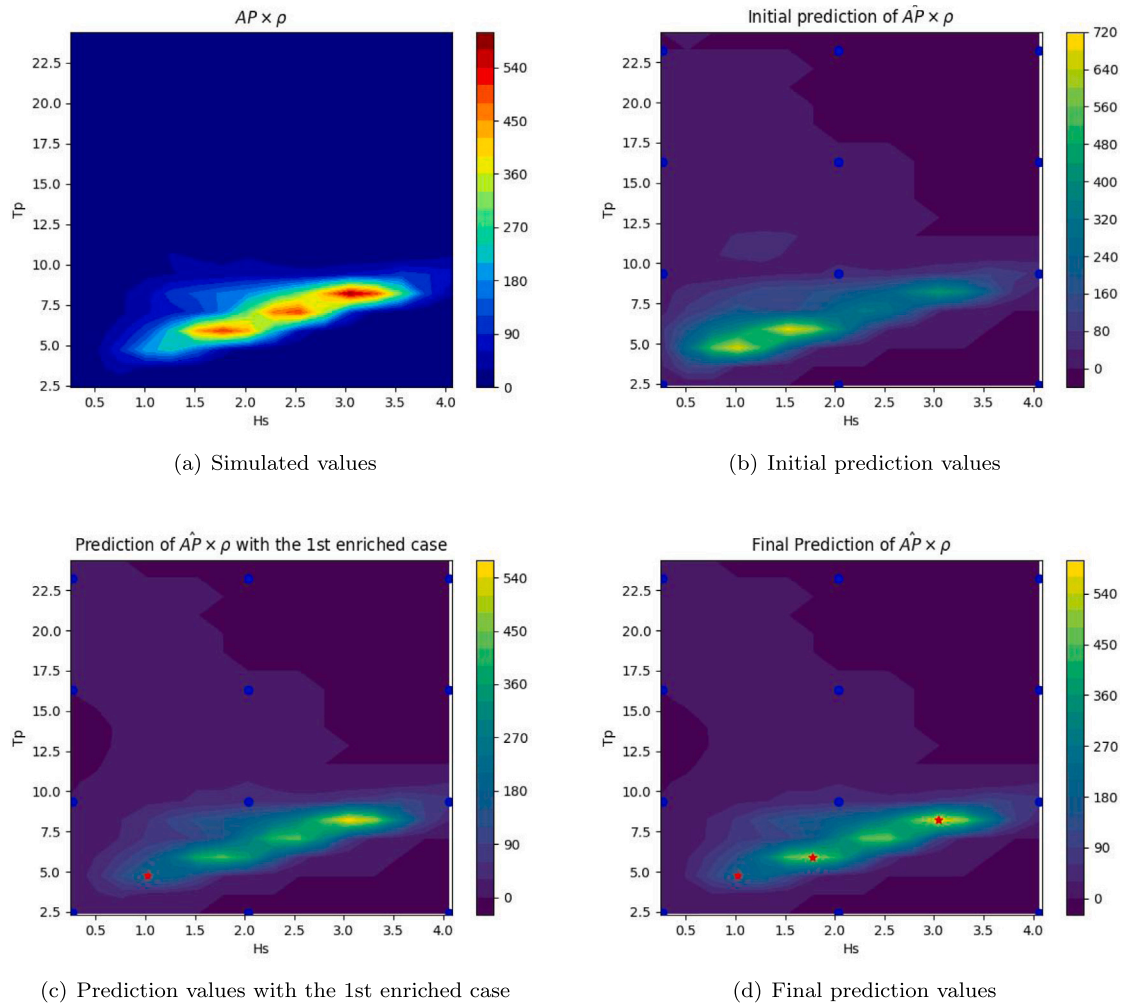


Fig. 10. Absorbed power prediction with the linear PTO system.

Table 3
Prediction results with the hydraulic PTO system.

Method	Hydraulic PTO	Simulated cases	Annual average value	Error (%)	Increased efficiency (times)
Numerical analysis	Absorbed power (W)	320	9169.43	–	≈ 21
	Equivalent fatigued load (N)		29 369.38		
Proposed AK method	Absorbed power (W)	15	9133.51	0.39	
	Equivalent fatigued load (N)		29 293.86	0.26	

methodology and the broadness of its applicability. In the future, the proposed method will consider fatigue loads of more components in WECs. Different types of wave converters will also be tested, and more offshore sites will be included. A wave energy converter optimization framework integrated with the proposed approach will be further developed.

CRediT authorship contribution statement

Jian Tan: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Chao Ren:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation,

Conceptualization. **George Lavidas:** Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition. **Yihan Xing:** Writing – review & editing, Supervision, Resources, Project administration, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

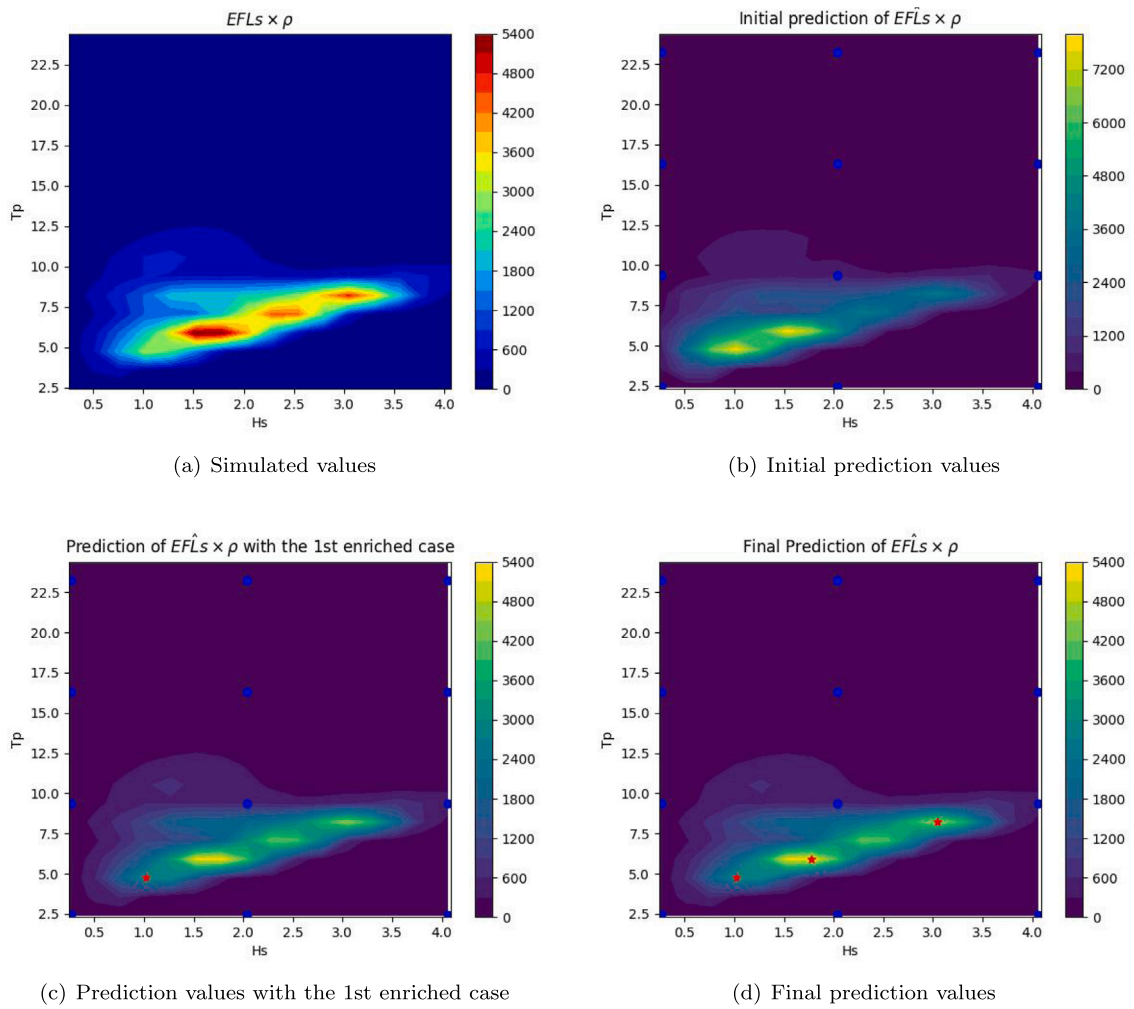


Fig. 11. Equivalent fatigue load prediction with the linear PTO system.

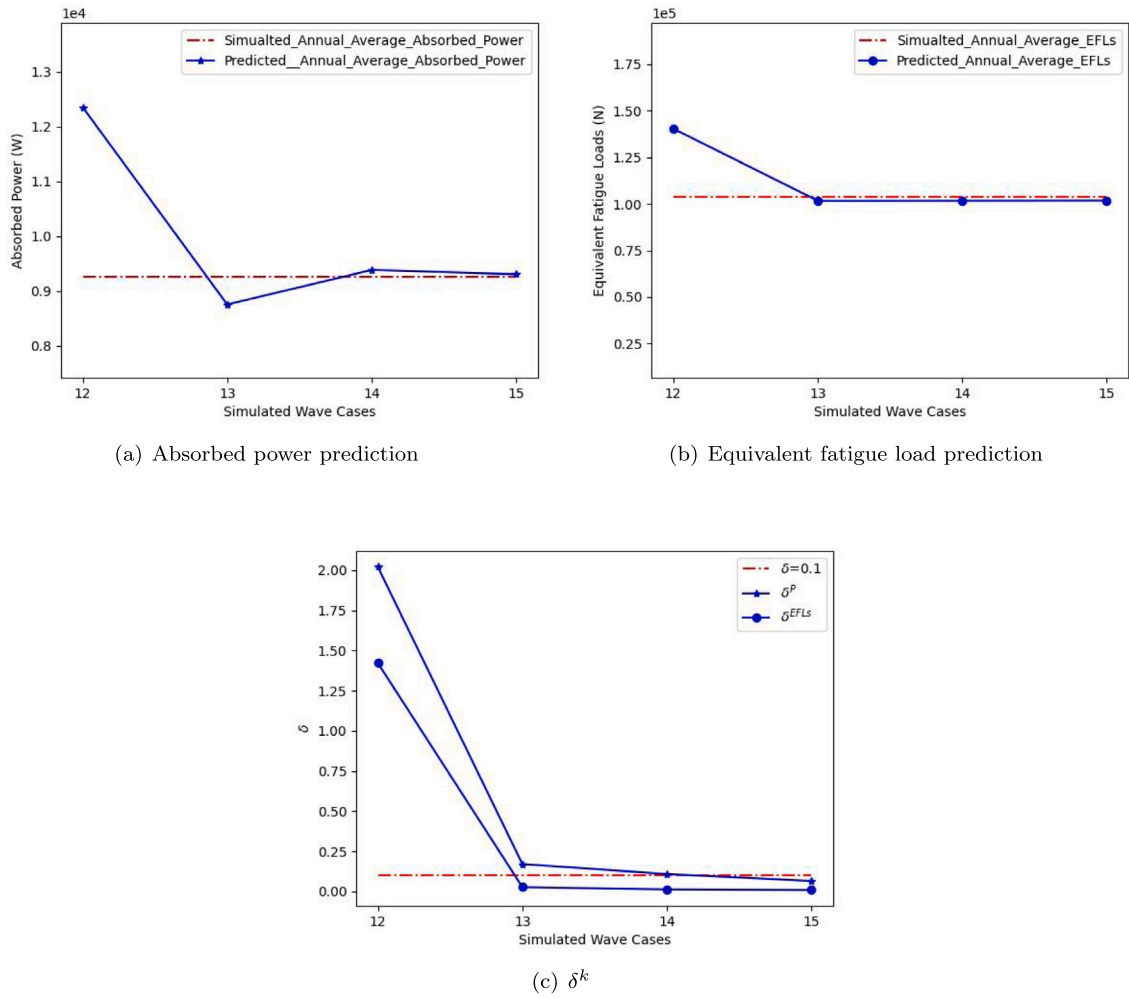


Fig. 12. Annual average prediction results with the linear PTO system.

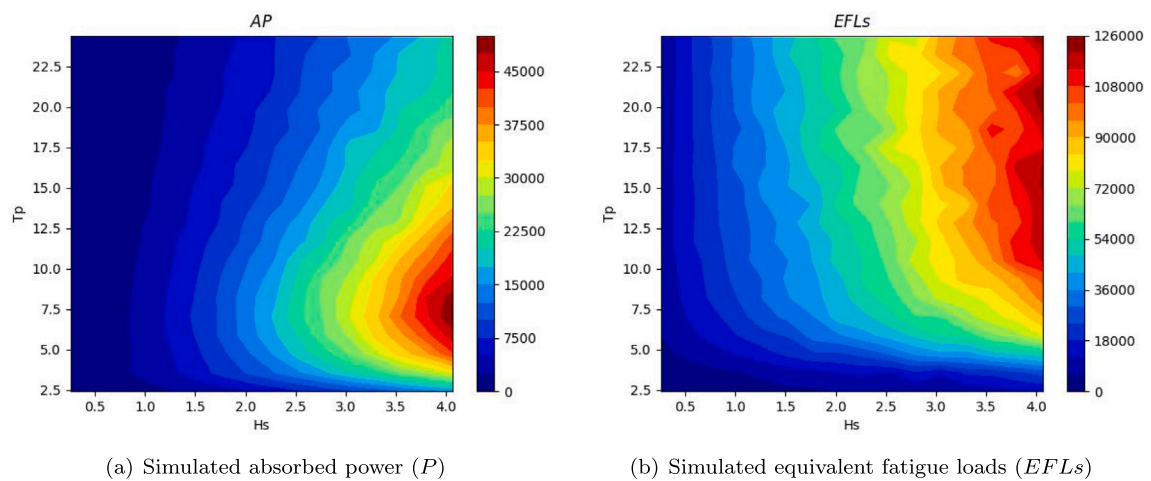


Fig. 13. Simulated results with a hydraulic PTO system.

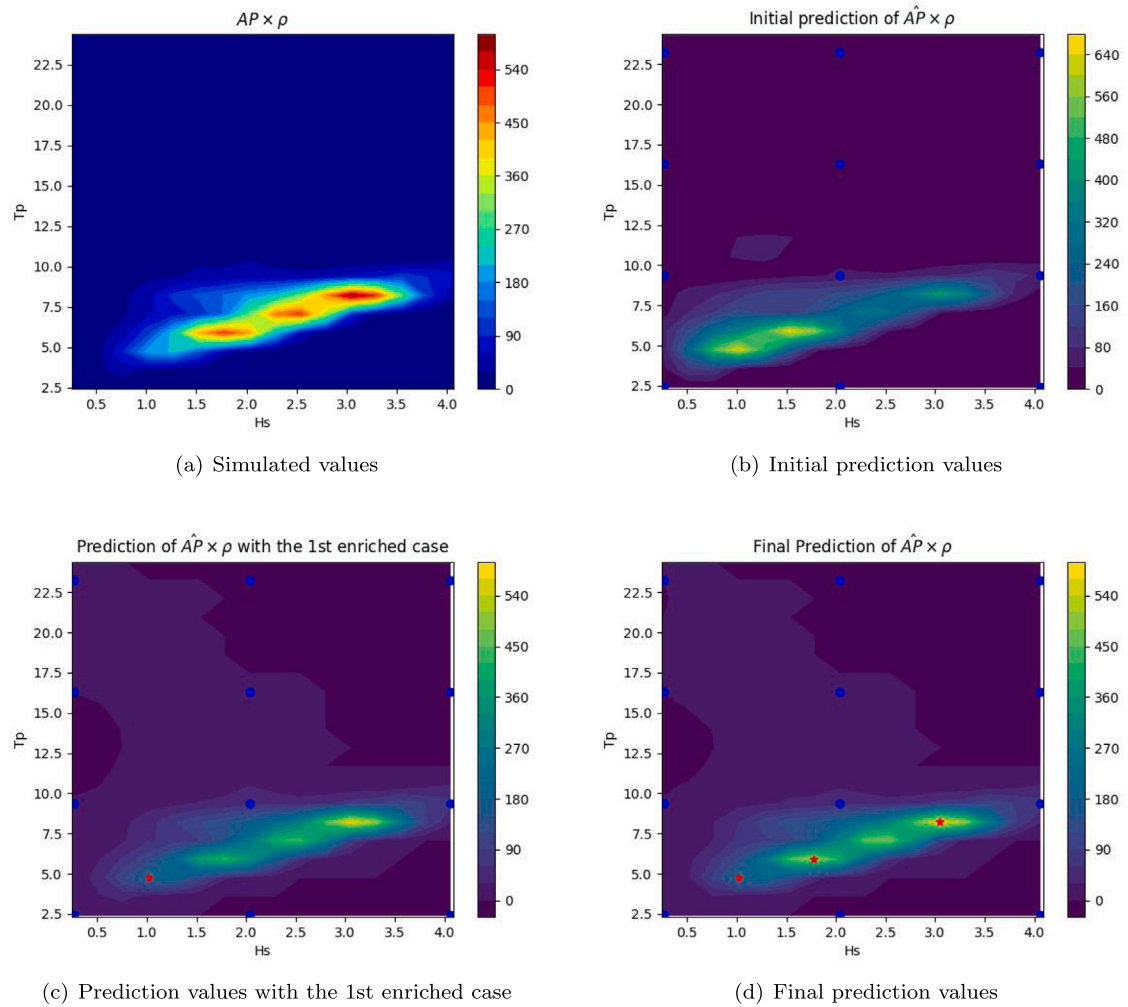


Fig. 14. Absorbed power prediction with the hydraulic PTO system.

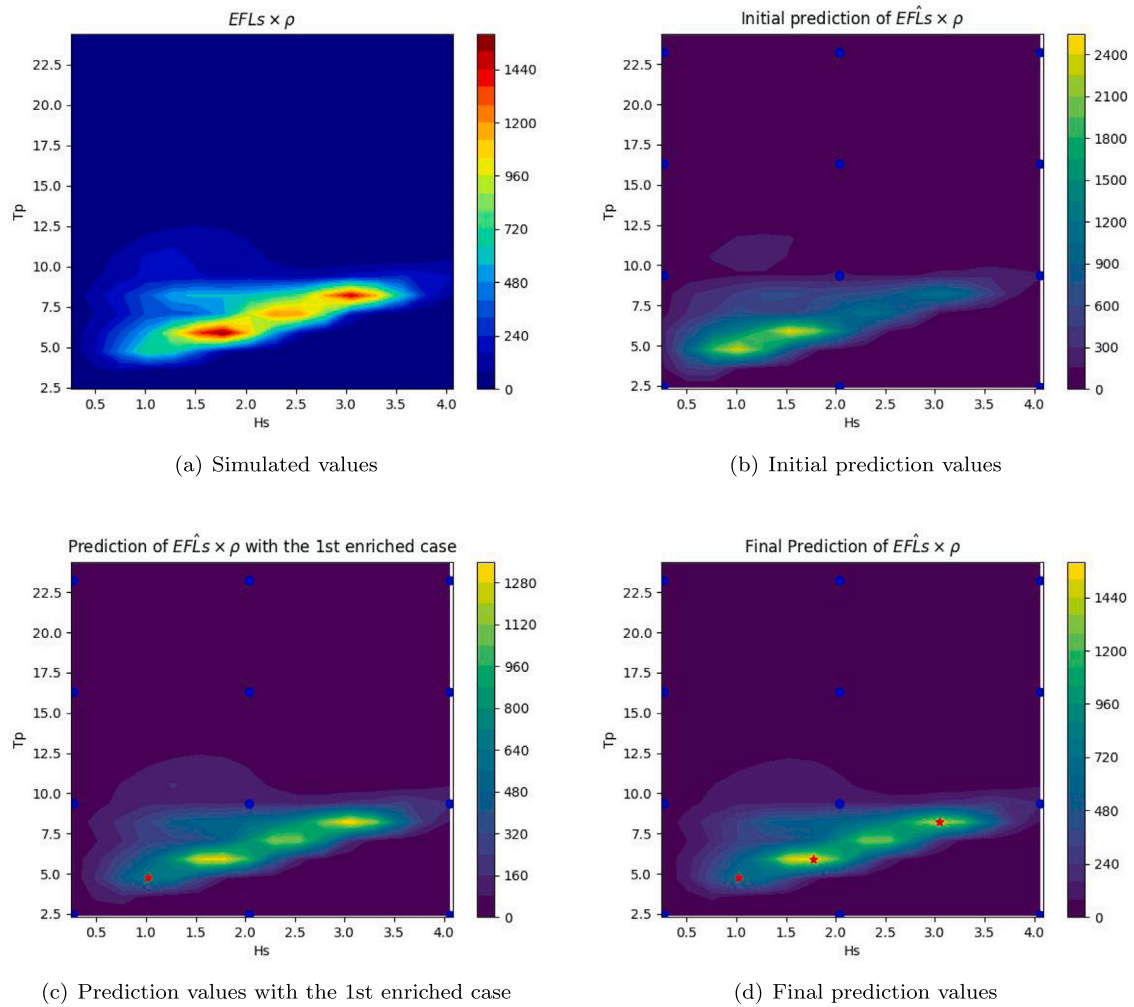


Fig. 15. Equivalent fatigue load prediction with the hydraulic PTO system.

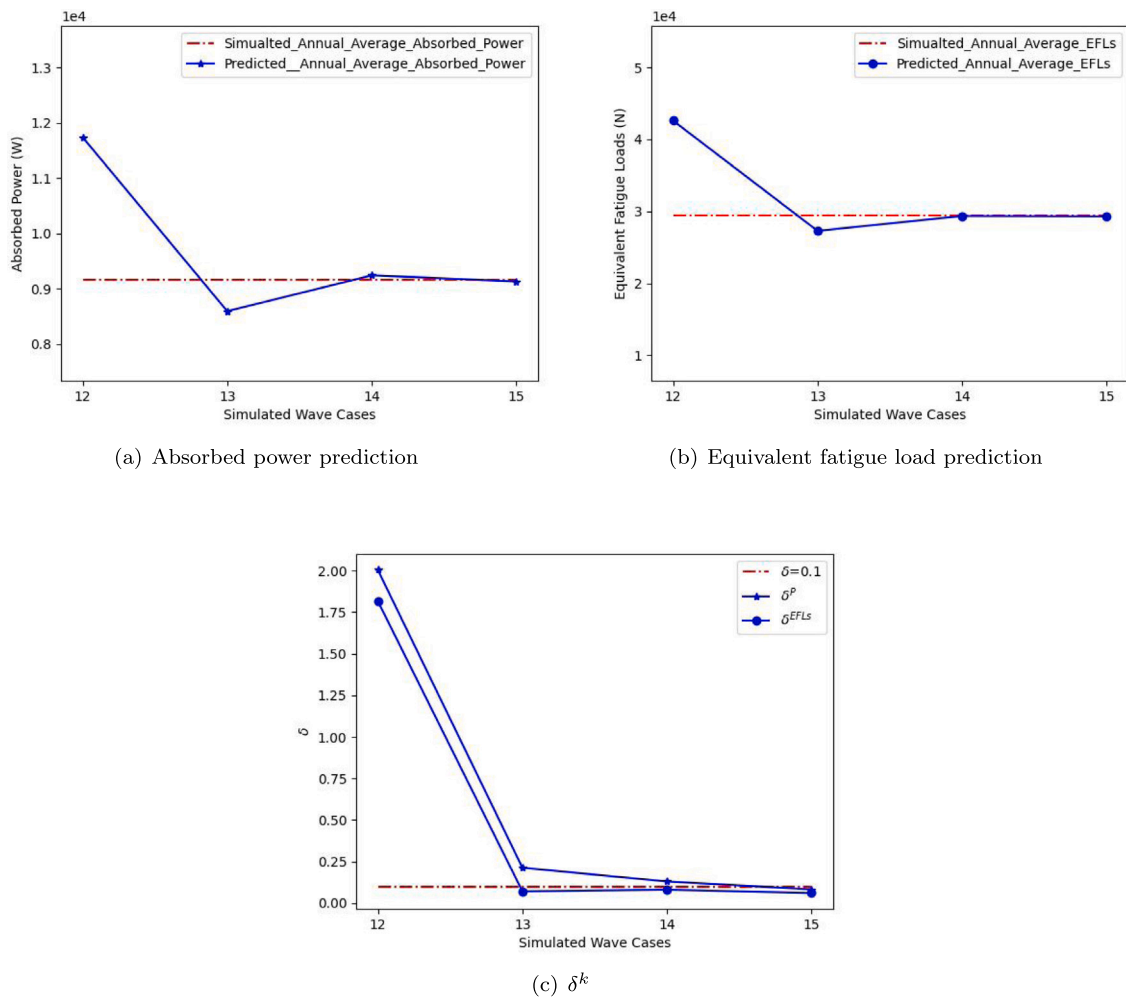


Fig. 16. Annual average prediction results with the hydraulic PTO system.

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