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On optimization-based strategies in data-driven control of wave energy systems

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ABSTRACT: To reach economic viability of *wave energy converter* (WEC) devices, the development suitable control logics is a fundamental step towards enabling commercial success. Given WECs nature, their control problem is of the *energy-maximizing* type. Control strategies are responsible of defining the proper control action, maximizing energy while ensuring safe operations. The computation of this action often requires an optimization process and the resulting control is said to be *optimization-based*. Usually, these optimizations require a control-oriented model of the system, which is prone to potential uncertainty sources. In this context, *data-driven* control strategies could provide a solution to the issues that usually characterize model-based logic. Motivated by this, we examine, in this paper, the fundamental relations between the concept of WEC optimal control, and the adoption of data in the optimization-based control computation, investigating intrinsic limitations, and highlighting consequences and opportunities this choice leads to in the design of such algorithms.

1 INTRODUCTION

In the context of renewable energy, *wave energy* is among the ones with most untapped potential (Mattiazzo 2019). In contrast to other sustainable energy solutions, like photo-voltaic (PV) or wind turbines, wave energy converters (WECs) have not reached technological maturity, with a consequent absence of any well-established concept for the wave energy conversion solution (Guo & Ringwood 2021). Trying to move in this direction, in the context of wave energy, several challenges have to be solved to efficiently capture all the energy that comes from waves motion. Among such challenges, one of the most crucial is the development of suitable advanced control strategies (Ringwood 2020), since this has a direct influence on the productivity and operational costs of WECs.

The control law must be able to adapt to the changes that the deployment (marine) environment features (in terms of excitation forces coming from the sea), while, at the same time, managing to maximize the energy extracted. Usually, the control strategies that are employed in wave energy rely on a (simplified) model of the system to compute the required control action and, for this reason, are termed within this paper as *model-based*. For ease of computation, such models are usually a linear representation of the system, which neglects the presence of nonlinear effects, and any potential nonlinear phenomena arising from its interaction with the environment, such as nonlinear Froude-Krylov forces (Giorgi et al. 2020). However, with the purpose of trying to overcome these simplifications, some novel strategies have tried to describe also the nonlinearities that could characterize the system in a control-oriented form (Faedo et al. 2020). Nevertheless, this type of approach is not free from other problems that characterize model-based strategies, such as the inherent presence of modeling uncertainty (Ringwood et al. 2020) due to the differences between model and real system, especially in any contribution related to hydrodynamics. As a consequence of these issues, an increasing interest can be observed for control strategies that can operate without the requirement of a system model (*model-free*) (Parrinello et al. 2020, Moens de Hase et al. 2021), or whose action is guided by data collected online, directly from the system (*data-driven*) (Anderlini et al. 2017a, Anderlini et al. 2020).

Motivated by the interest that this latter type of control is generating within the wave energy community, we analyze, in this paper, the relationship that occurs between the choice of exploiting data in the control strategy formulation, and the adopted strategy itself, whenever an optimization process is performed. In

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particular, in Section 2, the energy-maximizing optimal control problem that characterizes the WEC control is presented, together with a brief introduction to wave energy conversion. In Section 3, the data-driven control strategies, that adopt optimization in their formulation, are presented and analyzed, highlighting strengths and weaknesses. Finally, in Section 4, some considerations are made with respect to the possibilities and limitations that this type of approach could offer in the WEC control problem solution.

2 WEC OPTIMAL CONTROL PROBLEM

This section introduces the WEC control problem, highlighting the critical issues that an energy-maximizing strategy, including systems constraints, entails when applied in an environment continuously excited by external disturbances, such as in the marine case. In particular, the behaviour of an ideal WEC is presented in Section 2.1, together with the main equations describing its motion, while the energy-maximizing optimal control problem is formulated in Section 2.2.

2.1 *Wave energy converters modelling*

For the sake of simplicity of exposition, we consider a single[1] degree-of-freedom (DoF) WEC device throughout this paper, based on the schematic presented in Fig. 2.1. This type of device is commonly constituted by a floating hull, able to extract energy from a single DoF through the so-called *power take-off* (PTO) system (actuator), as it is possible to see in Figure 1[2]. The equation of motion for such class of devices can be given by[3]:

$$m\ddot{z} = f_r + f_{hr}^l + f_{ex} + f^{nl} - f_{PTO}, \tag{1}$$

where z is the device heave displacement, f_r is the radiation force, f_{hr}^l is the linear component of the hydrostatic restoring force, f_{ex} is the wave excitation force, f^{nl} represents a potential source of nonlinearity that depends on displacement z and velocity $\dot{z}$ (*e.g.* nonlinear hydrostatic effects or viscous drag forces), and f_{PTO} is the controllable force exerted by the PTO. Apart from f^{nl}, the terms in equation (1) are normally modelled based on potential flow theory. However, this representation is only an approximation that is easier to be treated by real-time control strategies. In fact, a variety of assumptions and associated set of approximations, are typically made when WECs are modelled for control

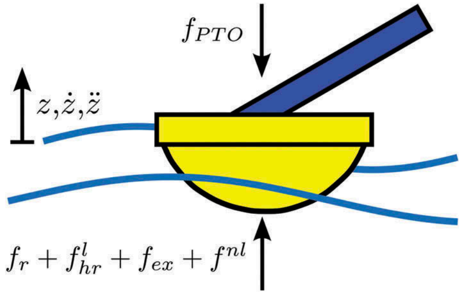

Figure 1. Simplified schematics of a WEC absorber.

purposes. As a consequence, several uncertainties are thus introduced, which can potentially influence the performance of the computed control action, whenever calculated through model-based control strategies.

2.2 *Energy-maximizing optimal control problem*

As already introduced in Section 1, the main goal of control strategies, in the WEC case, is the maximization of the energy absorbed over a certain time interval $\mathcal{T} = [a, b] \subset \mathbb{R}^+$. If mechanical power is considered (for the sake of simplicity), the instantaneous absorbed power is the product between the PTO force $f_{PTO}(t)$, and the device velocity $\dot{z}(t)$. In this way, the control objective $\mathcal{J}$ can be formulated as:

$$\mathcal{J}(f_{PTO}) = \frac{1}{T}\int_{\mathcal{T}} f_{PTO}(\tau)\dot{z}(\tau)d\tau, \tag{2}$$

where $T = b - a$. It should be remembered, however, that the goal is not only to maximize energy, but also to avoid the risk of damage to internal components, in an attempt to preserve the life of the entire device. With this aim, a set of limitations (*i.e.* constraints) is often introduced along with (2). In particular, it is usually possible to incorporate constraints on maximum displacement z_{max}, velocity $\dot{z}_{max}$ (Bacelli & Ringwood 2013), and control force $f_{PTO,max}$:

$$\begin{cases} |z| \leq z_{max}, \\ |\dot{z}| \leq \dot{z}_{max}, \\ |f_{PTO}| \leq f_{PTO,max}, \end{cases} \tag{3}$$

1 Note that similar arguments can be made for multi-DoF devices (see, for instance, (Folley 2016)).

2 It is important to highlight that here we decided to present all the modelling through a heaving device, but similar considerations can be done with different WEC working principles, and the following critical review of optimization-based strategies in data-driven control of wave energy systems include all wave energy system technologies.

3 From now on, the dependence on t is dropped when clear from the context.

with $\forall t \in \mathcal{T}$, and $\{z_{max}, \dot{z}_{max}, f_{PTO,max}\} \subset \mathbb{R}^{+}$. Hence, in the general case, the optimal control problem (OCP) can be fully written as

$$\begin{aligned} f_{PTO}^{\text{opt}} &= \arg\max_{f_{PTO}} \mathcal{J}(f_{PTO}) \\ &\text{s.t. :} \\ &\text{WEC dynamics}(1), \\ &\text{Motion and input constraints}(3). \end{aligned} \quad (4)$$

However, to perform the synthesis of the associated energy-maximizing controller, it may not be necessary to directly solve the OCP online. In the wave energy sector, in fact, there are two main categories of controllers: optimization-based and the non-optimization-based controllers (Faedo et al. 2020). Within the first category, one can find all strategies in which an optimization process is carried out online at some point of the control action computation. Relevant examples of this class, in wave energy applications, are *model predictive control* (MPC) (Li and Belmont 2014, Faedo et al. 2017, Bracco et al. 2020), *spectral* and *pseudo-spectral control* (Auger et al. 2019), (Garcia-Violini & Ringwood 2021), and *moment-based control* (Faedo et al. 2021). The second category, *i.e.* non-optimization-based control, encompasses those controllers that attempt to maximize the extracted power by 'emulating ' the so-called *impedance-matching* condition (Faedo et al. 2022) for maximum power transfer. An example is the *Linear Time Invariant Controller* (LiTe-Con) (Garcia-Violini et al. 2020, Carapellese et al. 2022). Despite the fact that this latter category has certain advantages, such as computational efficiency or ease of implementation, they struggle to guarantee constraint satisfaction in a straightforward fashion, and commonly provide the optimality condition on the basis of fundamental principles arising from the WEC equivalence with electric circuits, rather than from the numerical solution of (4). For this reason, and motivated by the interest in exploring the relationship that occurs between exploitation of a numerical optimization routine, and the usage of data in control synthesis, we focus our analysis on data-driven controllers that belong to the first class, *i.e.* data-driven optimisation-based controllers for WEC systems.

3 OPTIMIZATION-BASED WEC CONTROL: DATA-DRIVEN STRATEGIES

As stated in Section 1, the design of suitable control strategies for WECs is a crucial task in the development of economically viable solutions. However, at the same time, the WEC control problem is affected by the nature of the marine and ocean environments. These include, just to mention a few, the presence of a persistent and non-negligible exogenous disturbance force coming from the waves (*i.e.* the wave excitation f_{ex} in (1)), the difficulty of obtaining high-fidelity models with reasonable computational demands, and the need to adapt to an ever-changing environment, while trying to minimise the need for human intervention. Each of these issues corresponds to a challenge that the control strategy has to overcome:

1. The presence of a unmeasurable stochastic disturbance, i.e. f_{ex}, influences the complexity of the power absorption process and, consequently, the optimal control action that has to be computed (Merigaud & Ringwood 2018). This means that the wave contribution is crucial in every objective function that considers either energy, or power absorbed over a certain time, and that the control should be able to incorporate such information accordingly.
2. As mentioned in Section 2.1, modelling uncertainty needs to be managed in order to avoid possible potential controller misbehaviour that could lead to structural damage and/or suboptimal performance.
3. The control should respect any constraints that characterize the motion and velocity of the device, together with maximum control force available. Any damage would be difficult to repair in a prompt manner, and maintenance in offshore environments carries high expenses.

These strongly linked problems can be addressed differently depending on whether the control strategy chosen is model-based or data-driven. Model-based controls could be defined as control systems that base their synthesis on the knowledge of the plant to be controlled, based on a previously built model, which is fixed in time. This model can be obtained by means of first principle modeling or through system identification procedures (Schoukens & Ljung 2019). In contrast, we define data-driven control strategies as all those controllers which involve an *online* data flow that ultimately influences the control synthesis procedure (Hou & Wang 2013).

These two approaches lead to different strategies, each one with its advantage and drawbacks. In fact, the presence of a model can affect different aspects. In particular, through the knowledge of a model, it is possible, for example, to estimate the (unmeasurable) force f_{ex} acting on the WEC (Peña-Sanchez et al. 2020). As a consequence, in the optimization phase, the disturbance can be treated as known at every instant, and can be eventually forecasted over time through predictors (Peña-Sanchez et al. 2020). Having a model available during the synthesis phase of control also enables the propagation of the dynamics of the system into the future, thus enabling any constraints on system states and/or outputs (such as position or velocity) to be directly considered within the control computation. However, model-based strategies need to handle the inherent uncertainties

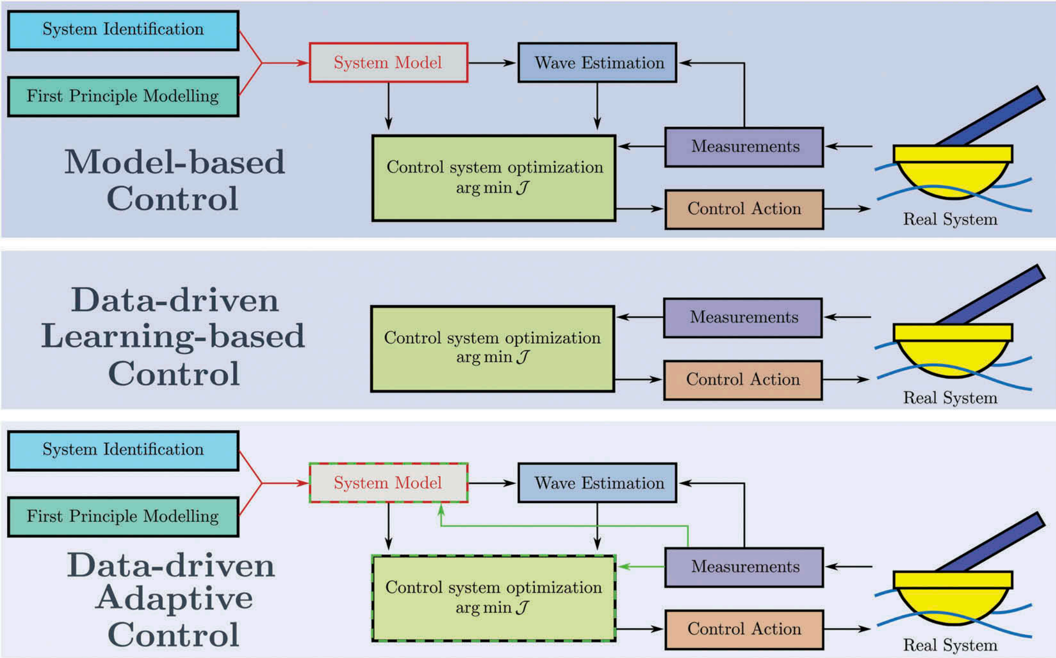

Figure 2. Optimization-based control working principles: the differences between model-based and data-driven approaches.

(parametric or given by unmodelled dynamics) arising from an approximate model of the system. In contrast, this problem does not affect the data-driven approach which, instead, having direct knowledge of the system from online data flow, can compute control actions based on the 'status' of the real system, or even adapting accordingly over time. Moreover, to have a higher fidelity, the model that model-based controls would require can compromise real-time feasibility and, consequently, deployability. These latter issues, typical of optimization-based systems with a model-based approach, generate a strong interest in exploring different data-driven solutions.

3.1 *Different types of data-driven optimization-based control systems*

The optimization-based data-driven control strategies applied in the wave energy field can be classified into two main classes: *learning-based* and *adaptive* strategies. As it is possible to notice from Figure 2, these approaches have two different working principles. In particular, the former relies on a learning process to calculate the optimal action to be applied. Online data flow impacts this process by directly changing the logic by which the control is computed, and the optimization process evolves. Adaptive strategies, on the other hand, exploit this flow of information to act on the knowledge they have of the system (a model), and modify the control synthesis process accordingly.

3.1.1 *Learning-based strategies*

Several state-of-the-art learning strategies have been considered to solve the WEC control problem. Among them, one main distinction can be made between algorithms that can be compared to *surrogate optimization* processes (Forrester & Keane 2009) applied to the optimal control problem, and those that fall into the category of *reinforcement learning* (Sutton & Barto 2018). All learning-based strategies are characterized by the need to balance the double goals of exploration and exploitation within their actions. In fact, these controls must be able to explore the space of actions to acquire enough information constituting their learned knowledge of the system, while, at the same time, maximizing energy absorption. For this reason, and in contrast to model-based control, these strategies must accommodate in some way a learning strategy within the control calculation phase, in order to balance these two 'conflicting' requirements. Moreover, another common characteristic, as it is possible to observe from Figure 2, is that they do not make use of wave estimation or any model of the system to solve the optimization problem.

Solutions belonging to the surrogate optimization-like category make use of a structure, often called a *metamodel*, to store the information obtained during the learning process. This structure is updated online and directly describes the map that associates the inputs (control actions and disturbance) of the system, with an estimate of the value that the function to be optimized takes under those conditions.

Among these strategies, a further distinction can be made with respect to the type of structure used to generate the metamodel. Neural networks (NN) have been used in (Anderlini et al. 2017a, Pasta et al. 2020) to formulate the relationship between the parameters describing the so-called reactive control (damping and stiffness feedback structure), and the significant height and energy period of the wave, with the measure of the function to be optimized. In (Pasta et al. 2020), the output is the absorbed average power over a certain time with the applied damping and stiffness, and in the measured sea condition. In (Anderlini et al. 2017a), an additional output is present to describe the maximum displacement, measured in the same time window corresponding with power averaging, to also consider, in the optimization process, constraint information. Also, (Pasta et al. 2021) adopts a NN to describe the metamodel, but the average power is connected, in this case, to the passive control parameter (damping), and those parameters characterising the corresponding sea-state (significant height and energy period). In all these three studies, the learning strategy is formulated purely as an initial exploratory phase (random values of damping and stiffness inside a certain bounded set), followed by a second stage in which the probability of additional exploration is inversely proportional to the amount of experience already gained. A second approach to the formulation of the metamodel is given by Gaussian Process Regression. The main advantage of this approach is that, since the Gaussian process is a probabilistic model, it is able to provide estimates of the uncertainty bounds with respect to the objective function that is modeling. This information is particularly valuable, providing the possibility of handling the balance between exploration and exploitation as an optimization process of a function called an acquisition function. The acquisition function weights the value given by exploration of areas with less knowledge (and highest uncertainty), with the benefit of adopting a control action that can potentially maximize the reward (areas close to the current best observation). In this way, through the optimization process itself, the control actions are exploration-oriented whenever the knowledge is insufficient, while, whenever the uncertainty of the metamodel reduces, these become exploitation-oriented instead. This approach is inspired by expensive function optimization algorithms, in which only a few attempts to observe the function to be optimized are available. This strategy is used in (Shi et al. 2019, Gioia et al. 2022) to converge to the optimal damping and stiffness of a reactive controller. The function to be optimized in (Shi et al. 2019)is the performance function of the WEC control competition (Ringwood et al. 2019), computed over a time window of 20 wave periods. This function rewards absorbed power, and penalizes large motions and PTO forces. In (Gioia et al. 2022), the function to be optimized represents average power, although the optimization process also exploits data provided by approximate model simulations of the WEC to accelerate convergence, in a *co-kriging* fashion (Forrester et al. 2007).

The second category is that constituted of reinforcement learning (RL) control systems (Sutton and Barto 2018). These algorithms belong to the class of unsupervised learning strategies, and base their convergence to the optimal control on the concept of learning through punishments and rewards, depending on the applied control actions and consequently observed results. In particular, in RL, an *agent*, in a certain state *s* (which describes the agent and the surrounding environment conditions), applies an action *a*, interacting with the environment and moving towards a new state *s'*. The consequence of action *a* is the reward *r*, which depends on the function that the optimal control wants to optimize. The selection process for *a* is modeled as a Markov decision process. This process is based on the so-called *value function*, which is an estimated value of the total future reward, with the aim to balance exploration and exploitation. The outcome of this strategy over time is the *policy*, *i.e.* the optimal behaviour the control is expected to learn. Several attempts have been made to adopt RL strategies to solve the WEC control problem. A first attempt to tune, online, a passive control law has been carried out in (Anderlini et al. 2016), adopting a Q-learning strategy. In (Anderlini et al. 2016), Monte-Carlo methods are applied to the formulation of the Q-learning strategy to deal with the variability that characterises irregular wave conditions, and to derive a declutching control strategy. In (Anderlini et al.2017c), the authors compared a *least-squares policy iteration* (LSPI) with Q-learning and SARSA (*state-action-reward-state-action*) approaches, to tune a passive controller aimed at maximizing average absorbed power. The same LSPI strategy is implemented, with some constraints considerations, in (Anderlini et al. 2017b) with the addition of a reactive (stiffness) term. Q-learning strategies are applied both in (Anderlini et al. 2018) and (Bruzzone et al. 2020) to obtain the optimal damping and stiffness of a reactive controller applied to point absorbers WEC systems. A deep Q-learning approach (that employs a deep neural network to describe the agent behaviour) is presented in (Umeda & Fujiwara 2020) and (Zou et al. 2022). Actor-critic versions of Q-learning have been employed in (Zadeh et al. 2020) and (Ghorban Zadeh et al. 2022). In particular, actor and critic are modeled as a NN in (Zadeh et al. 2020), and in a Bayesian fashion by means of GPR in (Ghorban Zadeh et al. 2022). It must be highlighted that the latter is the only attempt among these strategies to directly control the PTO force, and not a parametrization of a previously defined control law. However, at the same time, it must be pointed out that the excitation forces are assumed to be known in the process. (Ghorban Zadeh et al. 2022) also compares the results with an optimal model-based control (an MPC), showing the possible improvements obtained with respect to NN-based actor-critic Q-learning.

3.1.2 *Adaptive strategies*

The optimization-based adaptive strategy class comprises WEC control systems in which the online data flow affects the control synthesis by actively changing the adopted model of the plant, adjusting the structure over time to resemble the actual WEC process. As it can be seen from Figure 2 the presence of a model (even eventually from the initial stage, if an approximate model is assumed available) allows the use of wave estimators to provide estimates in time of the wave contribution. The interesting characteristic of this class is that, since a model is considered inside the optimization process that characterize the control synthesis, the adoption of well-established model-based techniques is thus enabled.

Since an online estimate of the wave disturbance can be considered available, this class of controls is mainly constituted by predictive control strategies. In particular, adaptive pseudo-spectral control is considered in (Davidson et al. 2017, Davidson et al. 2018). In these studies, leveraging a fixed model structure previously built through Jacobian linearization, the adaptive strategy controls the system while, at the same time, changing (online) the parameters of the model on the basis of data collected from the real system (emulated in this case by a high-fidelity numerical wave tank environment). In constrast, (Zhan et al. 2018) consider an adaptive parameter estimation algorithm to modify (online) the values of the radiation and excitation parameters, defined within a simplified model structure. The adapting model is employed within a linear noncausal optimal control strategy, able to synthesize the energy-maximizing control force. A similar adaptive approach is coupled with MPC in (Zhan et al. 2020). In this study, the authors adopted a parameter estimation mechanism to identify and update (online) the frequency-dependent dynamics terms of the model, allowing the MPC to suitably adapt to changes in either the system, or in the wave conditions.

It is important to note that, the control synthesis procedure is not the only valuable 'output'; These strategies are, in fact, able to provide a model of the system adapted using real online data, enabling also possible offline use for simulations with an improved fidelity.

3.2 *The problem of wave contribution*

One of the main differences between learning-based and adaptive strategies is given by the way in which they treat the disturbance, and minimise/effectively eliminate the variability introduced by wave effects. As mentioned in Section 3.1.1, learning strategies, not having an available wave force estimation process, usually consider statistical synthetic information of the wave signal (*e.g* energetic period and significant height), and base their objective function on an averaged measure of the power over longer time windows, reducing the variability given by the stochastic component of the wave in the absorption performance (Merigaud & Ringwood 2018). In contrast, adaptive methods suppose the presence of a simplified version of the system model. This facilitates wave estimation and the chance of explicitly considering the wave contribution in the power absorption, making the optimization problem to be solved deterministic. The possibility of wave estimation and forecasting allows the control synthesis to be based on shorter time windows, and a predictive approach to be adopted.

3.3 *What function does optimization fulfill?*

Another comparison between the different strategies can be made regarding the goal of the optimization process inside the control loop. In adaptive strategies, optimization provides the control action to be applied, *i.e.* giving, as an output, the actual control force able to solve the energy-maximizing problem. In learning strategies, instead, the output optimized by the controller is the parametrization of a fixed control law (usually a reactive or passive one). Moreover, having to deal with the presence of a learning strategy, another internal distinction can be made. Apart from the NN-based surrogate optimization-like algorithms, which treat the learning strategy in a separated fashion, all the other learning algorithms (GPR-based optimization-like and reinforcement learning) enclose the management of the learning strategy within the optimization process (and objective function). The resulting optimization goal includes, in this way, both energy maximization, and best learning.

3.4 *On the problem of constraint handling*

A final consideration can be formulated in terms of the capability of the analyzed control strategies to deal with different type of constraints. The relation that occurs between the choice of the strategy and the constraint handling mechanism is deeply influenced by model availability, and the way in which the control action is optimized (*e.g.* a predictive wave-by-wave approach, or an average approach purely based on past measured data). The presence of a model and the capability to ensure constraints are also mutually linked, since the latter is a consequence of the former. The presence of a model in adaptive controllers allows wave estimation (and consequently wave prediction through forecast methods), and the propagation of device dynamics into the future. This feature ensures the possibility of potentially considering both input and output (displacement and velocity) constraints in a specific (*i.e.* hard constraint) manner. In contrast, learning-based controllers, basing their entire knowledge of the conversion process on past average data, and not having any explicit prediction mechanism, are not capable of computing control actions that are able to guarantee hard constraint handling. Nevertheless, some attempts to include the constraint handling mechanism in the control design can be found within this class of controllers. For example, in (Anderlini et al. 2016, Anderlini et al. 2017c, Anderlini et al. 2018), the authors designed the reward function (to be maximized) in such a way that whenever the output constraints are not met, the obtained reward assumes a negative value. In this way, if the initial learning stage is performed in a simulated environment, once the controller is deployed on the real system it attempts to avoid any situation that can potentially cross the defined boundaries. In (Anderlini et al. 2017b), the reward function is also shaped to guide the system outside any situation of potential risk, but, in this case, by penalizing the reward value of a term that is inversely proportional to the distance of the maximum output in the evaluation, and the defined constraint value. A similar mechanism is adopted in (Shi et al. 2019), due to the fact that the objective function (assumed equal to the performance function of the WEC control competition (Ringwood et al. 2019)) already penalizes excessive velocities and displacements. Also, in (Ghorban Zadeh et al. 2022), the reward function penalizes the positive reward, given by high power absorption, in proportion to the constraint violation, whenever its maximum value is violated. Howver, in this works, the resulting control action could be very conservative, since controller parameters (*e.g.* damping and stiffness in reactive control) are reduced, making this approach an attempt to copy the constraint mechanism. Constraints are considered in (Zou et al. 2022) by means of a safety mechanism which, once the variable to be constrained crosses a certain safety value, make the RL-based controller switch to a controller designed to rapidly reduce the variable amplitude. Finally, in (Anderlini et al. 2017a), since the NN metamodel has a double output, constituted by average power and WEC maximum displacement, the optimization process is formulated to maximize the first output, while constraining the second. It is evident, however, that in explorative situations in which the control action (stiffness and damping parameters of the PTO reactive controller) is taken randomly, no attempt at constraint handling is present.

4 CONCLUSIONS

In this paper, we analyze the different data-driven optimization-based control solutions applied within the wave energy field. Two main classes of control, namely learning-based and adaptive WEC controllers, are identified, highlighting their own benefits and drawbacks. Within the current state-of-the-art, adaptive solutions offer a good trade-off between the intrinsic advantages offered by model-based control techniques (wave force estimation availability, hard constraint handling), while learning-based controllers have yet to overcome some of the problems that arise when any model is present within the optimization process. However, the opportunity to derive a control computation purely based on data is still very appealing for further research, mainly since it does not limit the internal system description to a model structure that has to be previously defined. This latter feature could be of crucial importance in real-world scenarios, where complex dynamical behaviour is present, which can be potentially missed by simplified control-oriented models, resulting in suboptimal energy-maximizing performance.

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