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Review article

Towards data-driven and data-based control of wave energy systems: Classification, overview, and critical assessment

Edoardo Pasta [a,*], Nicolás Faedo [a], Giuliana Mattiazzo [a], John V. Ringwood [b]

[a] *Marine Offshore Renewable Energy Lab., Department of Mechanical and Aerospace Engineering (DIMEAS), Politecnico di Torino, 10129, Corso Duca degli Abruzzi 24, Turin (TO), Italy*
[b] *Centre for Ocean Energy Research (COER), Department of Electronic Engineering, Maynooth University, Co. Kildare, W23 F2H6, Ireland*

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ABSTRACT

Currently, a significant effort in the world research panorama is focused on finding efficient solutions to a carbon-free energy supply, wave energy being one of the most promising sources of untapped renewable energy. However, wave energy is not currently economic, though control technology has been shown to significantly increase the energy capture capabilities. Usually, the synthesis of a wave energy control strategy requires the adoption of control-oriented models, which are prone to error, particularly arising from unmodelled hydrodynamics, given the complexity of the hydrodynamic interactions between the device and the ocean. In this context, data-driven and data-based control strategies provide a potential solution to some of these issues, using real-time data to gather information about the system dynamics and performance. Thus motivated, this study provides a detailed analysis of different approaches to the exploitation of data in the design of control philosophies for wave energy systems, establishing clear definitions of data-driven and data-based control in this field, together with a classification highlighting the various roles of data in the control synthesis process. In particular, we investigate intrinsic opportunities and limitations behind the use of data in the process of control synthesis, providing a comprehensive review together with critical considerations aimed at directly contributing towards the development of efficient data-driven and data-based control systems for wave energy devices.

1. Introduction

World energy demand has increased significantly over recent decades, making clean and efficient energy production one of the most crucial challenges. In the context of renewable energy, ocean wave energy has emerged as one of the most promising sources, having a vast (yet untapped) potential [1–3] of around 32 000 TWh/year [4]. In contrast to other renewable energy technologies, such as wind or solar, technology convergence has been slow among wave energy converters (WECs), with over 200 prototypes reported [5,6]. Among the challenges is the variability of the wave energy resource itself, with variations in amplitude and frequency [7], and directionality [8–10]. Moreover, the development of computationally modest mathematical models, given the complex hydrodynamic interactions between WEC devices and the surrounding fluid, is challenging [11,12]. There is also little agreement on the ideal power take-off (PTO) system to convert the physical WEC motion into useful energy.

Considering the increasing amount of available measurement modalities and continuously produced data, it is imperative that maximum advantage be taken of this information in the empowerment of renewable energy systems [13]. Possible applications of data-informed techniques can be found in solar, wind, and energy management fields for forecasting purposes [14–17], to model complex systems and scenarios [18,19], or to provide insight into previously unmodelled phenomena [20]. Data have been successfully employed in control applications to solve the control problems related to energy [21,22], and multi-energy distribution systems [23] management, and floating wind [24] and photovoltaic system control [25]. Within the marine energy field, most data-based techniques used are aimed at solving the problem of estimation of the wave source spectral characteristics [26], predict their trends over time [27–29], forecast wave elevation

* Corresponding author.
E-mail address: edoardo.pasta@polito.it (E. Pasta).

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Nomenclature

Abbreviations

ANN	Artificial neural network
DB	Data-based
DB1	Data-based, type I
DB2	Data-based, type II
DD	Data-driven
DD1	Data-driven, type I
DD2	Data-driven, type II
DD3	Data-driven, type III
DoF	Degree of freedom
ESC	Extremum seeking control
GPR	Gaussian process regression
MPC	Model predictive control
MPPT	Maximum power point tracking
NL	Nonlinear
OCP	Optimal control problem
OWC	Oscillating water column
P&O	Perturb & observe
PA	Point absorber
PTO	Power take-off
RL	Reinforcement learning
WEC	Wave energy converter

Symbols

η	Wave elevation [m]
$\mathcal{J}$	Control performance function
$\mathcal{T}_P$	Prediction horizon [s]
E	Absorbed energy [J]
f_r	Radiation force [N]
f_{hr}^l	Hydrostatic restoring force linear component [N]
f_{nl}	Nonlinear contributions [N]
f_{PTO}	PTO force [N]
m	WEC mass [kg]
S_η	Wave elevation spectrum [m^2 s]
t	Time [s]
T_s	Sampling period [s]
$T_{\mathcal{J}\mathrm{eval}}$	Performance evaluation period [s]
$T_{\mathrm{ctrl.\ synth.}}$	Control synthesis period [s]
$T_{\mathrm{ctrl.}}$	Control period [s]
$T_{\mathrm{data\ gen.}}$	Data generation period [s]
$T_{\mathrm{mdl.\ adapt.}}$	Modelling/adaptation period [s]
$v_{ref.}$	Velocity reference [m/s]
y	General output of the system
z, $\dot{z}$, $\ddot{z}$	Heave displacement [m], velocity [m/s], and acceleration [$\mathrm{m/s}^2$]

[30–32] and forces on the devices [33–35], and to (partially) model the hydrodynamic interactions [36].

In the drive towards improved economic performance, control technology has been identified as a significant contributor [37]. The wave energy control problem is to maximise absorbed energy, while respecting the physical limits (displacement, force, etc.) of the WEC system. For this reason, its solution actively contribute to the final productivity of wave energy systems, and to their operative costs, also indirectly addressing, in a Sustainable Development Goals framework [38], the Goal 7 which is to 'ensure access to affordable, reliable, sustainable and modern energy for all' [38]. In addition, the effective control of WECs is seen as an important solution towards the societal challenge of mitigating climate change [39]. For WEC systems, most control strategies are model-based, with models typically simplified to make them analytically/computationally tractable. However, in recent decades, there is increasing interest in the use of system data in the control synthesis process. The diversity of uses depends on the characteristics of the control strategies which make use of data, and the different approaches these lead to, depending on their availability, control aim, and type of application [40–43]. Given the specific nature of the WEC control problem, we comprehensively investigate the main strategies that exploit data in the wave energy control synthesis process, especially given the difficulty in producing high-fidelity tractable models from first principles. Basing the controller development on data obtained from the real system (or high-fidelity models) can potentially address the challenge of designing effective WEC controllers. Currently, few informed guidelines on the effective incorporation of data in WEC control processes are available in the literature. Motivated by this, and by the overall discussion provided immediately above, this paper provides the following main contributions and objectives:

- To provide clear preliminary definitions and a classification of the different control techniques in wave energy which exploit data, highlighting how the relationship between data and control (and the assumptions about these two) changes the way the controller functions, including the design of the controller itself.
- To highlight advantages and disadvantages of each of the considered types of 'data-informed' controllers, providing an exhaustive review of the applications of these strategies in the wave energy field, and clear guidelines on the appropriate solution choice for a given context and objective.
- To detail the next steps towards efficient data-informed control of WEC systems, showing the research needs to successfully guarantee reliable utilisation of this kind of strategies in realistic WEC systems.

The remainder of the paper is organised as follows: Section 2 briefly introduces WEC working principles and WEC modelling. Section 3 describes the WEC control problem, including the role of mathematical models in the synthesis process. A brief overview of common model-based strategies, together with their limitations, are also presented. Section 4 connects control design with the potential use of data in the wave energy field, providing a classification system and a clear distinction between data-based and data-driven control, individually detailed within Sections 5 and 6. Section 7 critically compares different types of controllers constituting the data-based and data-driven classes, highlighting the opportunities and pitfalls of each approach. Finally, Section 8 draws conclusions and provides potential research directions to further the design of WEC controllers based on, or driven by, data.

2. WEC systems technology

WEC devices contain both an absorber body, converting hydrodynamic potential and kinetic energy into mechanical energy, and a PTO system that further converts this mechanical energy into a useful form, typically electrical [7,44,45]. In general, it is possible to classify wave energy systems on the basis of their geometries and working principles [45,46] into four main classes [46]: Point absorbers (PAs) [47], oscillating water columns (OWCs) [48], terminators [49–51], and attenuators [52].

2.1. WEC modelling

For simplicity, to introduce WEC dynamics, we consider a single[1] degree of freedom (DoF) WEC point absorber device, based on the

[1] It is important to note that, even if a heaving WEC is considered, similar arguments can be formulated for different multi-DoF devices (see, for instance, [53]).

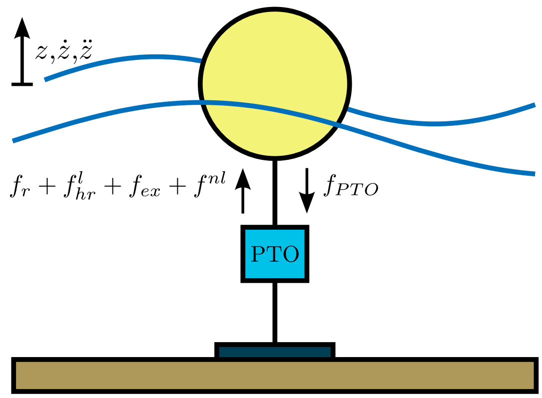

Fig. 1. Simplified schematics of a WEC point absorber.

schematic presented in Fig. 1. These devices typically consist of a floating hull, able to extract energy from a single DoF by means of the PTO system (actuator), as shown in Fig. 1. The equation describing the motion of such type of devices can be formulated as[2]:

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

where z is the device heave displacement, f_r represents 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 non-linearity (e.g. those depending on displacement z and velocity $\dot{z}$, such as nonlinear hydrostatic effects, mooring, or viscous drag forces [54]), and f_{PTO} is the (controllable) force exerted by the PTO. With the exception of f^{nl}, the terms in Eq. (1) are usually modelled following linear potential flow theory [53] (assuming linear wave theory, small oscillations, and inviscid and irrotational flow).

The radiation force is typically modelled using Cummins' equation (see [55]), while the wave excitation force f_{ex} is characterised in terms of standard stochastic descriptions in the field of marine/ocean engineering (see e.g. [56]). Due to the random nature of the wave force, the consequent power absorption process is inherently non-deterministic [57]. Assuming linear potential flow, both excitation and radiation effects can be computed in terms of boundary element method solvers, such as Nemoh [58].

The simplifying assumptions used for control-oriented modelling, associated with linear potential flow theory, introduce a certain degree of error [59]. Additionally, the application of controllers based on such assumptions, may directly invalidate these hypotheses. Specifically, linearised models assume small device motion, but the application of WEC optimal control strategies virtually always maximise absorbed energy by exaggerating the motion, leading to the so-called WEC 'modelling paradox' [12], further amplifying the inherent modelling error. As a result, these errors can influence the performance of model-based controllers [60].

3. WEC energy-maximising control problem

As mentioned in Section 1, the main control objective is the maximisation of the energy the device absorbs over a certain time interval $\mathcal{T} = [a, b] \subset \mathbb{R}^+$. Considering (mechanical) absorbed energy, a suitable performance metric is:

$$\mathcal{J}\left(f_{PTO}\right) = \frac{1}{T}\int_a^b f_{PTO}(\tau)\dot{z}(\tau)d\tau, \tag{2}$$

where $T = b - a$. Other performance metrics are also possible, ideally with a view towards minimisation of the levelised cost of energy. To avoid exceeding physical system specifications, constraints can be included in the optimisation process. Through maximisation/minimisation of the performance function, it is possible to deal with such limitations (e.g. on maximum displacement z_{max}, velocity $\dot{z}_{max}$, and control force f_{PTO} [61]) by means of soft constraints (minimising in an average fashion excessive values that should be constrained, or minimising the violation of the boundaries) or with hard constraints (always ensuring that the variables to be restricted belong to a defined set). Soft constraints can be implemented via additional terms $\mathcal{J}_{SC}$ (e.g. proportional to the squared norm of z_{max}, $\dot{z}_{max}$, and/or f_{PTO}) within $\mathcal{J}$ as:

$$\mathcal{J}\left(f_{PTO}\right) = \frac{1}{T}\int_a^b f_{PTO}(\tau)\dot{z}(\tau)d\tau + \mathcal{J}_{SC}, \tag{3}$$

Hard constraints can, instead, be introduced along with Eq. (2), as:

$$\begin{cases} |z(t)| \le z_{max}, \\ |\dot{z}(t)| \le \dot{z}_{max}, \\ |f_{PTO}(t)| \le f_{PTO,max}, \end{cases} \tag{4}$$

with $\forall t \in \mathcal{T}$, and $\left\{z_{max}, \dot{z}_{max}, f_{PTO,max}\right\} \subset \mathbb{R}^+$, leading to a constrained optimisation problem. There may be additional constraints on the grid side [62], while a flow coefficient, in the OWC case [63], has also been considered. In the general case, the optimal control problem (OCP) to be solved by the energy-maximising controller can be written as:

$$\begin{aligned} f_{PTO}^{\text{opt}} = \arg\max_{f_{PTO}}\ & \mathcal{J}\left(f_{PTO}\right) \\ \text{s.t.:}\ & \\ & \text{WEC dynamics (1)}, \\ & \text{Motion and input constraints (4)}. \end{aligned} \tag{5}$$

The solution of the OCP in (5) is dependent on the nature of the system mathematical model employed, trying to achieve a balance between fidelity and analytical/computational complexity [37], the control freedom permitted by the set of constraints in (4), and the nature of the wave excitation [57], noting that the ocean presents an ever changing environment. Ideally, the control philosophy should:

- Take maximum advantage of information regarding f_{ex},
- Be relatively insensitive to errors in the system dynamical model, where model-based control is employed,
- Strictly respect the system physical constraints in (4), since off-shore repairs are expensive [64], and
- Require as little user intervention as possible.

Ultimately, the control philosophy changes significantly, depending on the information available at the design stage, e.g. a WEC model or a set of data.

3.1. Outline of standard WEC control approaches

In the WEC control literature, a wide variety of control strategies have been reported [65], with the objective of solving the OCP presented in Section 3. One categorisation observes the dichotomy of optimisation-based and non-optimisation-based controllers [66]. The first category includes all controllers that require numerical optimisation to be performed online for the control action to be calculated, including e.g. model predictive control (MPC) [67,68], spectral and pseudo-spectral control [69,70], and moment-based control [71]. For a survey of the main WEC control strategies belonging to this category, the reader can refer to [72]. The second type, i.e. non-optimisation-based control, includes all controllers aiming to reach the maximum power transfer by trying to emulate the so-called impedance-matching condition [73–75]. Relevant examples of this type of controllers are given by the linear time invariant controller [75,76], which tries to

[2] From now on, the dependence on t is dropped when clear from the context.

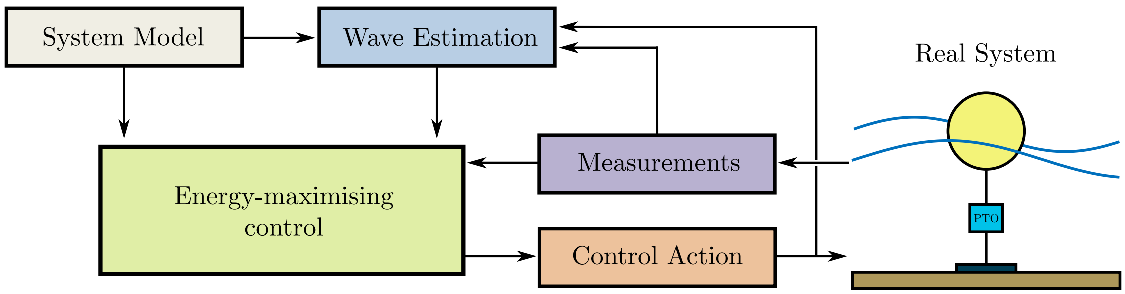

Fig. 2. Typical WEC control system: Schematic representation of the control loop.

approximate the impedance-matching condition for a band of frequencies according to the operating conditions of the WEC system under analysis, and by linear quadratic Gaussian control [77,78], designing an optimal causal controller for a WEC by solving a non-standard linear quadratic Gaussian OCP.

3.2. The role of models in WEC control

Most solutions to the control problem in Section 3 are model-based and, in general, rely on a fixed model, obtained by means of first principle modelling or through the use of off-line system identification procedures [79]. Such a model can be used within the control design procedure for a number of purposes, including estimation of the force f_{ex} acting on the WEC [80], which is otherwise unmeasurable. Consequently, the disturbance can be considered in the optimisation stage as 'known' at each instant, and can also be predicted using forecasting methods [30,81]. In addition, models allows the system dynamics to be propagated into the future, enabling direct hard constraint handling during the control computation. The role of WEC models in the synthesis process of typical controllers for wave energy systems is shown in Fig. 2. However, the achievable model-based control performance is a direct function of the employed model fidelity. The inevitable modelling errors (parametric or from unmodelled dynamics), if severe, could lead to unpredictable behaviour of the device, and even cause damage. On the other hand, high-fidelity models may not permit a control solution in real time. We note that, where system identification is used on-line to tune the model, a reasonable level of model fidelity may be achievable across a wide range of operating conditions.

Motivated by the issues associated with a controller purely based on an approximated model, we explore, in this study, the opportunities and pitfalls that arise from the exploitation of data of various types in the control synthesis for WEC applications.

4. WEC control and data: Definitions and classification

Control strategies in wave energy, which make use of data in their synthesis, can be distinguished by the way in which data are collected and treated, and on the role that data have in the overall process.

This variety of possible interactions between data and control results in different approaches, for example leading to (rapidly) adaptive control systems, or in fixed control laws with control parameters that adapt slowly over time to the environment around and the (possibly varying) plant itself. Included in this plethora of possibilities are the set of model-based controllers, formulated and/or adapted using real-time WEC data.

To classify these data-based (or data-driven) strategies, preliminary definitions are formulated, which constitute part of the contributions of this work, in Sections Section 4.1, and 4.2, respectively. It is important to highlight that, in the formulation of such definitions and classifications, an effort is made to provide general formulations, even if the focus of the work is specifically on wave energy control applications.

4.1. Definitions: Modelling, adaptation, storage, and control synthesis

In the analysis of the inter-relation between the control system and system data, the primary definition relates to data itself. In this context, data can be defined as any kind of information that is generated from the process to be controlled, usually describing the system reaction to the application of an external action (controllable or uncontrollable input), under certain condition and within a specific time frame.

Regarding the utility of data in controller synthesis, different stages can be identified. Each stage has a specific role and goal, and their implementation affects the final control outcome, its capabilities, and characteristics. In particular, we identify modelling, model adaptation, control synthesis, and data storage stages:

- Modelling: The stage in which, given a set of data, a dynamical model of the system is developed. The techniques used to perform this task usually fall under the moniker of system identification.
- Model adaptation: The process in which an already developed model is modified (entirely, or partially, e.g. in some of its parameters, if a parameterisation is present) to better reproduce the data gathered online when the system is operating.
- Control synthesis: The process of generating a structure (i.e. a parametrised law, or a process) that produces the control action, given the available information (i.e. a model, a dataset, or a single data point).
- Data storage: The selection and ordering of data that are needed in the development of the controller, from the set of measured data. This operation generates a dataset that is dynamical (i.e. it changes with time) whenever it is fed (also) by data that are generated online after an initial control synthesis has been performed; otherwise, the obtained dataset is static. In the dynamic case, part of the data storage process is the application of a suitable forgetting strategy, aimed at keeping a (reduced) representative set of data, avoiding potential overflow, or insensitivity to new data, during system operation.

Not all the above stages are always present. A modelling stage may, as already noted in Section 3.2, increase the capabilities of the developed control. Also, a data storage stage, 'keeps track' of the system 'experience' in terms of data, constituting a memory of past operation.

These definitions can also include the different time scales at which these operations are performed. Measurements from the WEC system, and/or incident waves, constitute the raw data logged at every sampling instant $t = kT_s$, with $k \in \mathbb{N}^+$. To generate the dataset that is (ultimately) adopted during the control synthesis, certain preprocessing operations (e.g filtering, averaging, etc.) can be applied. In particular, final data are generated every $T_{data\ gen.}$, while a measure of the performance function $\mathcal{J}$ can be produced every $T_{\mathcal{J}\ \mathrm{eval.}}$. These latter two periods usually coincide (i.e. $T_{data\ gen.} = T_{\mathcal{J}\ eval.}$). Equally, whenever modelling and/or adaptation stages are present, these are performed every $T_{mdl.\ adapt}$, while a new controller is synthesised every $T_{ctrl.\ synth.}$. The controller, however, produces a new control action every $T_{ctrl.}$. The

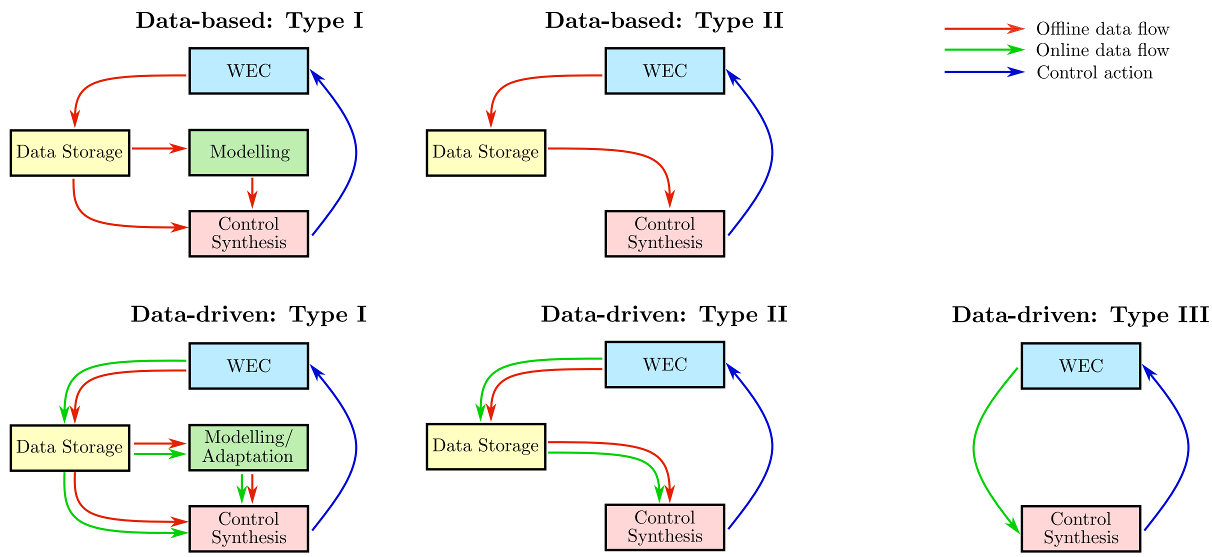

Fig. 3. Classification of DB and DD control systems in wave energy: working principles and data flows.

sampling periods, as defined above, can be related by the following simple inequality:

$$T_s \leq T_{ctrl.} \leq T_{data\ gen.} = T_{\mathcal{J}\ eval.} \leq T_{ctrl.\ synth.} \leq T_{mdl.\ adapt}. \quad (6)$$

It is important to notice that the control action is not necessarily applied at the same pace instruments generate raw data, and for this reason, $T_s \leq T_{ctrl.}$. The same holds for $T_s \leq T_{data\ gen.} = T_{\mathcal{J}\ eval.}$, since the preprocessing operations to generate the final data or measure $\mathcal{J}$ may require multiple raw measurements.

As detailed within Sections 4.4 and 4.5, these inequalities hold for all the controllers analysed in this study, and the specific values attached to these periods is strongly related to the type of control strategy that is consequently designed.

4.2. Definitions: Data and data flow

Data can be produced in different ways. An obvious way is to measure some (output) variables from the real system (process) to be controlled, when the system is operating. This type of data gives information on the overall system which has a degree of uncertainty defined only by any effect that pollutes the data itself (e.g. noise or measurement resolution of the instrumentation). A second path to obtain data is by means of system simulation, exploiting a previously formulated model. In this case, the uncertainty on the information obtained is given by the fidelity of the adopted model (higher fidelity → lower uncertainty).

A second clarification relates to the offline and/or online data available during controller synthesis:

- Offline data: Stored data produced from a different stage with respect to control synthesis.
- Online data: Data employed and/or stored at the same rate (in time) as their generation.

As a consequence of such definitions, whenever an online data flow is present in a strategy that adopts a data storage stage, the resulting dataset is effectively a dynamical dataset.

Depending also on the data usage, additional requirements can be present. For example, whenever data are adopted to generate a model of the process to be controlled, these must satisfy the so-called fundamental lemma by Willems [82], related to concept of persistence of excitation [82–85]. The lemma has clear implications for system identification, and data-based modelling. stating a condition for the data to be sufficiently informative to uniquely identify the system model within a given model class.

4.3. Classification system: Data-based and data-driven control

A fundamental distinction between controllers making use of data relates to the type of data flows holds between data-based (DB) and data-driven (DD) control strategies, specified by Hou and Wang [40] for general classes of control applications.

- DB control makes use of a static dataset, without any sort of online data flow involved.
- DD control adopts a dynamical dataset and, for this reason, an online data flow is present in the process.

In the DD case, the adoption of a dynamical dataset does not exclude the presence of offline data, obtained before the control synthesis stage, which can be augmented by online data flow, affecting future controller synthesis stages.

4.4. Classification of controller types

A second distinction between the considered controllers can be formulated on the basis of the activities and stages relating to control synthesis. With reference to Section 4.1, three distinct types of control strategy can be identified:

- Type I: Strategies that assume the performance of a modelling, and/or a model adaptation, stage on the basis of a stored (static or dynamic) dataset prior to the control synthesis stage.
- Type II: Strategies which need past (and eventually present) data to be stored, but nevertheless do not assume any modelling and/or a model adaptation stage to synthesise the controller.
- Type III: Strategies which perform control synthesis at every $T_{data\ gen.}/T_{\mathcal{J}\ eval.}$, purely on the basis of the information produced online at the present instant, and without any form of modelling, data batch, or storage involved.

Combining the definitions given to DB/DD classes (Section 4.3) and controller types (Section 4.4), five classes of controller can be identified:

- Data-based, type I (DB1).
- Data-based, type II (DB2).
- Data-driven, type I (DD1).
- Data-driven, type II (DD2).
- Data-driven, type III (DD3).

A graphical representation of the working principles and data flow, characterising the different classes and types of controllers identified, is shown in Fig. 3. Since Type III control strategies exploit only present data (unique to DD control) to perform control synthesis (thus involving only an online data flow), no DB Type III controller can be formulated.

4.5. Classification system: Relationship between time scales, classes, and types

Having presented the classification system in Sections 4.3 and 4.4, some considerations can be made regarding the set of inequalities in Eq. (6). Indeed, the identified classes are strongly related to the values assumed by the different periods/scales defined in Section 4.1. The first distinction is related to the broad DB/DD classes. As a starting point, $T_{ctrl.\ synth.}$ can be taken as infinite for all DB controllers, since control synthesis is performed only once, offline, before deployment. The same happens in the case of DB1 control systems with $T_{mdl.\ adapt}$ (note that DB2 does not include any modelling stage). In contrast, for DD controllers, both $T_{ctrl.\ synth.}$ and $T_{mdl.\ adapt}$ are finite.

Also in DD control, $T_{\mathcal{J}\ eval.}/T_{data\ gen.}$ and $T_{ctrl.\ synth.}$ are strongly linked, being identical in DD3, in contrast to most of the controllers in DD1 and DD2. Since DD3 does not involving a storage process, the controller is (re)synthesised every time new data is generated. In DD1 and DD2, the data can be effectively stored, allowing a disparity in timescales between control synthesis and data production.

Finally, the relationship between $T_{\mathcal{J}\ eval.}$, $T_{ctrl.}$, and T_s is related to the way in which the control strategies resolve the issues of stochasticity introduced by the wave disturbance and constraint handling. Since the DD2 and DD3 strategies are model free, a process of averaging and filtering in the evaluation of $\mathcal{J}$ is required, to reduce the variability of the absorbed energy given by a realistic ocean wave [57] over a relatively short timescale. The definition of $\mathcal{J}$ as a function of the average value of past measurements, requires $T_{\mathcal{J}\ eval.}$ to be longer than $T_{ctrl.}$ and T_s.

Similarly, displacement, velocity, and control action constraints in DD2 and DD3 are accommodated in an average sense, with penalty term usually added to $\mathcal{J}$. This constraint handling approach is naturally more conservative than employment of hard constraints and requires careful tuning to guarantee constraint satisfaction across the complete operational space. In contrast, DD1 strategies, which adopt a WEC model, enable wave contribution estimation and exact constraint handling, without the need of an averaging approach. For this reason, in DD1 control, usually $T_{\mathcal{J}\ eval.} = T_{ctrl.}$.

4.6. Classification system: Considered works

In the proposed classification and survey, studies in which data are effectively adopted in the synthesis of the WEC control strategy are considered. For this reason, considering that the field of predictor design which makes use of time-series forecasting [30,32,86,87], is effectively data-based, we consider only those studies in which data are directly responsible for either the control synthesis procedure itself, or involved in building the model on which the entire synthesis process is based, not considering the studies in which data are used only to tune an already synthesised control strategy, e.g. [88].

5. Data-based control

As presented in Section 4, DB control strategies adopt a static dataset, used to effectively 'develop' the control solution. Within DB control, two main types of controllers are present: DB1, which makes use of data to build the model on which the control strategy is designed, and DB2, which employs the produced data to directly 'develop' the controller, avoiding any modelling stage. In particular, DB1 strategies employ data to reduce the uncertainty present in the model employed for control synthesis. In DB2, in contrast, the use of data is often aimed at reducing the complexity of the synthesised control system, or replicating the behaviour of controllers that, because of computational requirements, could only be deployed in simulated environments.

5.1. Data-based (DB) control: Type I

DB1 accommodates all the control strategies which adopt a model built offline from datasets compiled from previous tests or experience. Since the model is developed from data, rather than first principles, all the control systems synthesised from a system identification process [79] fall under this category. Moreover, since data are used only once offline during the identification stage, control synthesis can be achieved using well-established model-based techniques, unlimited by data management requirements. As a consequence, model-based synthesis more easily attracts guarantees of stability and convergence, not always easily (or fully) demonstrated in the case of model-free control strategies [41].

While system identification techniques have became popular in recent years in the wave energy field [54], a comprehensive review of all studies concerning this topic is beyond the scope of this work, which is primarily focused on different control applications based on, or driven by, data. Nonetheless, in the remaining part of this section, a brief overview of the main studies on the subject is presented, in an attempt to provide the reader with insight on the (DB1) data-based approach to WEC control-oriented modelling. For reviews of model-based WEC control strategies, the reader is referred to [65,72,89–91].

In the wave energy field, a comprehensive study on the application of system identification, in the wave energy context, is presented in [92,93], including the design of identification-oriented tests to be performed on a point absorber in a numerical wave tank [92], together with the consequent development of control-oriented models, using different black-box identification methods [93]. Similar tests are employed to perform grey-box identification in [94]. In [95], system identification is performed to find a state-space model of a point absorber, subsequently employed by a predictive fuzzy logic controller [96]. In [97], identification-oriented multisine signals are designed to perform experimental tests on a scaled WEC, with the resulting responses used to identify a black-box model of the system. A scaled multi-DoF WEC model is also identified from experimental tests in [98], and the obtained model is adopted to synthesise different energy-maximising control strategies, subsequently experimentally assessed. In [99], a nonlinear reduced-complexity model is determined following a data-based moment-matching approach, on the basis of simulated data. Data obtained in a simulated environment are also adopted in [100], where a nonlinear control-oriented WEC model, including nonlinear Froude–Krylov effects [101], is identified and subsequently employed to synthesise a moment-based control solution. In [102], recorded tank test data are used to identify nonlinear Kolmogorov–Gabor models. Applications of system identification techniques to experimental data from tests on scaled OWC devices can be found in [103,104], where the authors identify the dynamical relationship between free-surface elevation and water column displacement inside the OWC chamber. In [105], the same dataset is used to model the OWC dynamic system describing the turbine pressure drop between the chamber and atmosphere, driven by the variation in free-surface elevation. In [106], a parametric model of the dynamics of a point absorber is obtained from wave tank tests, and used to synthesise a Linear Time Invariant Controller strategy, which is then experimentally assessed. The studies in [59] investigate the process of identifying a model from data obtained in a numerical wave tank, exciting the system with different classes of signals, evaluating the uncertainty on the obtained models, and assessing the performance of a corresponding robust control strategy. In [107], the influence of the excitation amplitude in the process of system identification is highlighted, with similar wave tank experiments. Finally, in [108], identification-oriented signals are applied to a WEC coupled with a mooring system (usually neglected in control-oriented models) in a simulated environment, and a corresponding empirical frequency response estimate is used as representative non-parametric linear description of the system to synthesise a reactive controller.

Table 1
Summary review table: data-based control-oriented modelling studies. The studies under analysis are divided on the basis of the type of data adopted in the system identification process, which could be the result of a numerical simulation (Sim.), or of experimental tests (Ex.).

Ref.	Type of data		WEC type
	Sim.	Ex.	
[93]	●		PA
[92]	●		PA
[94]	●		PA
[95]	●		PA
[97]		●	PA
[98]		●	PA
[99]	●		PA
[100]	●		PA
[102]		●	PA
[103]		●	OWC
[104]		●	OWC
[105]		●	OWC
[106]		●	PA
[59]	●		PA
[107]	●		PA
[108]	●		PA

Table 1 summarises the studies discussed within this section, highlighting the source of data and type of WEC considered. In general, when experimental data are not available, identification data are computed from high-fidelity simulation environments, including effects (such as nonlinear hydrodynamics or mooring dynamics) which are otherwise neglected if standard linearisation approaches are adopted in a physics-based modelling stage.

5.2. Data-based control: Type II

DB2 constitutes control strategies which are directly synthesised offline from a static dataset, without any preliminary modelling stage. All the strategies belonging to this category exploit data in an attempt to solve some of the issues related to the adoption of optimisation-based control strategies that make explicit use of models (see also the discussion provided in Section 3.2). In particular, DB2 controllers are often synthesised from data obtained in simulated environments, where limitations given by real-time computational capabilities are not present/considered. In such cases, the controller is optimised to replicate an optimal control solution that would not be implementable in practice, due to its potentially prohibiting computational burden.

An example of a controller synthesised from simulated data is shown in [109], where a nonlinear MPC strategy (presenting substantial computational requirements) is first applied in a simulated environment, and the obtained controller data are used to train an artificial neural network (ANN) to mimic the nonlinear MPC behaviour. The ANN output layer activation function is designed to guarantee the same constraint on the control action as the original MPC. In [110], the optimal velocity profile for a PA constrained in heave displacement, which is shown to be quadratic, is solved in simulation, with the produced data used offline to synthesise a controller able to generate (online) the optimal velocity to be tracked. The study in [111] analyses a controller based on an ANN trained on simulated data from an OWC model. The controller obtained computes an optimal velocity reference able to avoid the stall condition [119], and its performance has been experimentally assessed on a hardware-in-the-loop facility. In the studies [63,112,117], and [116], ANNs are also adopted to control OWC reference velocity in constrained conditions. Advancing further, [63,117] constrain the turbine flow coefficient [48], while [112,116] bound the grid active, and reactive, power signals in an attempt to avoid voltage dips faults [120]. Another application of an ANN is proposed in [113], in which the parameters of height and spread describing the Gaussian neurons of the network are optimised using an evolutionary algorithm in a simulated environment. Such a trained network guides a time-varying damping to maximise the extracted energy. In [114,115], a biologically inspired ANN, termed a central pattern generator, is used to define the latching period of a latching control law [121]. The ANN (which tries to replicate the neurological system that controls the locomotion mechanism of lampreys) weights are optimised offline to maximise the absorbed power, using simulated data. Finally, in [118], an ANN is used to approximate the solution (which is not available in closed-form) of a nonlinear non-causal optimal control strategy. Network training (and consequent weight optimisation) is performed offline by means of a policy iteration mechanism, on the basis of data coming from the application of the original control law in simulated irregular wave conditions.

To compare the studies detailed to this point (and also those presented in the following sections), a summary table with all the considered characteristics (legends described in Table 2) is offered in Table 3. Alongside each corresponding classification, each reference has been evaluated in terms of the type of control law (i.e. direct control action, reference velocity to be tracked, or parametrised controller), constraint handling capabilities (input/output constraints, and if constraints are treated in a soft or hard manner — see the discussion provided in Section 3). Moreover, since one of the issues to be solved within the WEC control problem is the inclusion of any kind of information related to the wave disturbance, we highlight the way in which this is treated by each study. In addition, any proofs of convergence and stability are also highlighted, to underline eventual opportunities for further theoretical development on the reviewed control strategies. Finally, the design complexity (considered in terms of number of parameters to be designed) is detailed, together with the conditions under which each strategy has been assessed (i.e. simulation with linear/nonlinear model and/or experimental tests, type of waves adopted, and device class), and the performance of an optimisation process in real-time during the computation of the applied control action.

Regarding the DB2 studies discussed within this Section, we note that all the analysed studies employ some sort of ANN to synthesise the controller. In particular, these networks are ostensibly used to mimic a strategy that is considered optimal (e.g. biologically inspired networks which mimic the behaviour of real fish in [114,115], or a deep neural network which mimics a nonlinear MPC in [109]). From Table 3, note that none of the DB2 strategies perform online optimisation. The entire control synthesis is performed once offline, and the data-based approach is adopted precisely to avoid real-time implementation of what can be a potentially prohibiting control solution. Finally, it can be highlighted that, in a field like wave energy, in which obtaining data in a controlled environment is not trivial, DB2 strategies, potentially coupled with high-fidelity simulation, can (at least partially) provide a solution to the issues related to the modelling uncertainty linked to the (usually linear) approximation of WEC hydrodynamics [11,12]. Data obtained following this methodology can also be employed in direct control synthesis approaches based on data [122,123] which, in other renewable energy applications, such as wind energy [124], are already well-established.

6. Data-driven control

As defined in Section 4.3, DD control strategies adopt a dynamic dataset, continuously updated using an online data flow (see also Fig. 3). DD strategies can be divided into three main classes (DD1, DD2, and DD3), depending on the presence of a model, and the adoption of a data storage mechanism prior to the control synthesis, as discussed in Section 4.4. It is important to highlight that this classification already reflects well-known classes of controllers [125]: (Indirect) adaptive

Table 2
Reference guide to read Tables from 3 to 7.

Column	Brief description
Ref.	List of reviewed studies.
Type	Classification of the control strategy, *i.e.* DB1, DB2, DD1, DD2, DD3.
Control	Type of control law that the study proposes: • f_{PTO}: Output of the control strategy is the direct optimisation of the PTO force. • v_{ref}: Output of the control strategy is the optimisation of the WEC reference velocity. • Par.: Control law that describes the f_{PTO} is parametrised, and the output of the control strategy is the optimisation of the parameters characterising it.
$\mathcal{J}$	Type of objective function that the control strategy under study tries to optimise: • $f(E)$: Objective function that depends directly and only on the absorbed energy. • $f(E,\cdot)$: Objective function that depends directly on the absorbed energy, but includes other terms/goals. • Oth.: Objective function that depends indirectly on absorbed energy (*e.g.* on physical considerations that attempt to drive the WEC into maximum absorption conditions), or on other terms/goals.
Constr. handl.	Way in which the constraints on f_{PTO} (control force) and on measured outputs y (like position z, velocity $\dot{z}$, etc.) are handled: • Nothing: The analysed study does not mention any constraint handling. • ◆ (soft): Constraint handled in a soft manner. • ◆ (hard): Constraint handled in an hard manner.
f_{ex}, η know.	Strategies that involves the knowledge of the excitation force f_{ex} or wave elevation η: • S_η: Strategies that exploit the knowledge of the wave elevation spectrum S_η, or of some of its characteristics, *e.g.* energetic period T_e, peak period T_p, or significant height H_s. • t: Strategies that exploit the knowledge of f_{ex}, η at the current instant (either via estimators or by assuming full knowledge). • $\mathcal{T}_P$: Strategies that exploit the knowledge of f_{ex}, η over a time window of future instants (either via predictors or by assuming full knowledge).
RT opt.	Studies involving the online solution in real-time (RT) of an optimisation problem to compute the control action.
Proof	Studies that report a proof (analytical and/or numerical) of convergence (Conv.) and/or stability (Stab.), or that at least refer to studies reporting such proofs for the control strategy under study.
Design compl.	Design complexity of the control strategy under study (in terms of design parameters): • 🟩: The strategy presented in the study involves the design of 1 to 4 parameters during the control development. • 🟨: The strategy presented in the study involves the design of 5 to 8 parameters during the control development. • 🟧: The strategy presented in the study involves the design of 9 to 12 parameters during the control development. • 🟥: The strategy presented in the study involves the design of more than 12 parameters during the control development.
Res. eval.	Conditions in which the study assesses the strategy performances: • L: Performance is assessed by means of a linear model of the WEC system. • NL: Performance is assessed by means of a nonlinear model of the WEC system. • Ex.: Performance is assessed by means of experimental results.
Wave eval.	Studies that tested the proposed strategy under regular (R) and/or irregular (I) wave conditions.
WEC type	The type of WEC that is adopted in the studies (as described in [46]): • PA: Point absorber. • OWC: Oscillating water column. • Ter.: Terminator. • Att.: Attenuator.

Table 3
Summary review table: DB2 studies.

Ref.	Type	Control			$\mathcal{J}$			Constr. handl.		f_{ex},η know.			RT opt.	Proof		Design compl.	Res. eval.			Wave eval.	
		f_{PTO}	v$_{ref.}$	Par.	$f(E)$	$f(E,\cdot)$	Oth.	y	f_{PTO}	S_η	t	$\mathcal{T}_P$		Conv.	Stab.		L	NL	Ex.	R	I
[109]	DB2	●				●			◆ (hard)		●					🟨		●			●
[110]	DB2		●		●			◆ (hard)		●	●				●	🟨	●				●
[111]	DB2		●		●			◆ (hard)								🟨		●	●	●	●
[63]	DB2		●				●	◆ (hard)		●						🟩		●		●	
[112]	DB2	●				●		◆ (hard)						●	●	🟨		●		●	
[113]	DB2			●	●						●			●		🟨	●			●	●
[114]	DB2			●	●									●		🟩	●			●	
[115]	DB2			●		●								●		🟨	●				●
[116]	DB2		●				●	◆ (hard)						●		🟨		●			●
[117]	DB2		●				●	◆ (hard)		●						🟨		●		●	
[118]	DB2	●				●		◆ (soft)	◆ (hard)		●	●		●	●	🟧		●			●

Table 4
Summary review table: DD1 studies.

Ref.	Type	Control			$\mathcal{J}$			Constr. handl.		f_{ex},η know.			RT opt.	Proof		Design compl.	Res. eval.			Wave eval.	
		f_{PTO}	$v_{ref.}$	Par.	$f(E)$	$f(E,\cdot)$	Oth.	y	f_{PTO}	S_η	t	$\mathcal{T}_P$		Conv.	Stab.		L	NL	Ex.	R	I
[130]	DD1	●				●		◆	◆		●	●	●	●	●	■	●		●		●
[131]	DD1	●				●		◆	◆		●	●	●	●	●	■	●				●
[132]	DD1		●				●	◆			●	●	●	●	●	■	●				●
[133]	DD1		●				●	◆			●	●	●	●	●	■	●				●
[134]	DD1			●	●			◆	◆		●	●	●			■		●		●	●
[135]	DD1		●		●			◆	◆		●	●	●	●		■		●			●
[136]	DD1		●		●			◆	◆		●	●	●	●		■	●	●			●
[137]	DD1	●					●				●	●				■		●			●
[138]	DD1	●				●		◆	◆		●			●	●	■	●				●
[139]	DD1	●				●		◆	◆		●			●	●	■		●			●
[140]	DD1	●				●		◆	◆		●			●	●	■	●				●
[141]	DD1	●			●			◆	◆		●	●	●			■		●			●

control strategies [126] are allocated to DD1, learning-based control [127] is in DD2, while extremum-seeking control (ESC) [128] and maximum power point tracking (MPPT) [129] controllers constitute DD3. Note that DD3 has no equivalent in the DB controller class, existing only due to the presence of online data flow.

6.1. Data-driven control: Type I

DD1 accommodates all the strategies that make use of a modelling, or model adaptation, stage using a dynamic dataset prior to the control synthesis stage. In this way, during operation, data affect the control synthesis process by actively acting on the adopted model of the plant, and the corresponding evaluation of $\mathcal{J}$ over time, reflecting both the actual WEC process and its estimated performance. As detailed in Section 3.2, the presence of a model enables the incorporation of wave estimation and forecasting tools (and, consequently, the possible inclusion of the wave contribution in $\mathcal{J}$). For this reason, most of the strategies belonging to DD1 are predictive control strategies.

Examples of DD1 predictive controllers can be found in [135,136], developing adaptive pseudo-spectral control for a point absorber. These strategies exploit a fixed model structure previously built by means of Jacobian linearisation of first principles equations, and perform online adaptation of the parameters of a model on the basis of data collected from the real system (which, in the case of [135,136], is the WEC simulated in a high-fidelity environment). In [132,133], a previously built first principle model is adopted, and the uncertain parameters related to mechanical and hydrodynamic effects are adapted online following an exergy minimisation approach. Such a continuously adapted model is used to generate an optimal velocity reference to be tracked, in a standard cascade loop fashion. Similarly, in [130], an adaptive parameter estimation algorithm continuously modifies (online) the radiation and excitation parameters within a simplified model structure, and the resulting model is employed to synthesise a linear non-causal optimal control strategy. A comparable adaptive parameter estimation mechanism is employed in [131], to identify and update online frequency-dependent parameters in a WEC model, subsequently used by a MPC strategy to adapt to possible changes in the system or wave conditions. A nonlinear MPC strategy is also developed in [141], where the model is built using a Gaussian process [142] representation from data obtained online. This continuously updated model, claimed to have low computational requirements, is used to perform real-time optimisation required by the nonlinear MPC. A nonlinear model is repeatedly built from online data using an ANN in [137], and then used, after an inversion process, to compute the corresponding optimal control action. In [134], a model is continuously identified online and utilised in the optimisation of a fuzzy logic controller [96] while, in [138–140], an adaptive dynamic programming [143] approach is used to control a point absorber. The strategy adopts a model of the system, and uses data to adapt online the optimal cost value, in an attempt to reduce the error given by the mismatch between model and real system, potentially improving the energy absorption capabilities of the controller. Table 4 presents a summary of the reviewed studies, confirming the diversity of approaches within this category.

Table 4 demonstrates that all the reviewed strategies exploit information regarding the present contribution of the wave, possible due to the availability of a WEC model (as discussed before in Section 3.2), characteristic of this category. Moreover, with the exception of [138–140], all DD1 strategies assume availability of future wave information. The use of such knowledge, typical of predictive controllers, allows hard constraints (both on the outputs and corresponding control action) to be handled, as clarified in Table 4. Finally, we note that, in DD1 strategies, the model provides an additional output (that can also be exploited offline for other purposes, such as simulation or performance assessment). Given the nature of wave energy systems (which are continuously excited even in uncontrolled scenarios), the fundamental lemma [82] on the need of persistent excitation holds, allowing the process of identification and adaptation which characterise DD1 controllers. In [131–133,135,136], the output is an adapted model, coming from an initial system obtained from first principle modelling. Other studies, such as [137,141], do not adapt a model, but generate a new one from the data produced online. Finally, [138–140] adapt an additional contribution (the critic in the adaptive dynamic programming field), whose adaptation is used to compensate the mismatch between data and model of the system. All these approaches aim to mitigate the problem of modelling error that characterise control-oriented WEC models, combining the advantages of direct system information and model-based strategies.

6.2. Data-driven control: Type II

DD2 consists of all the control strategies employing a dynamic dataset containing past and present data to synthesise the control system, without incorporating any modelling or model adaptation stage. The data is used to gather ‘past experiences’ in a process of ‘learning’ towards optimal control. Consequently, this category of controller contains a structure able to exploit the past experiences within a learning process, by suitably linking the actions taken by the controller with their consequences on $\mathcal{J}$. This structure tries to provide information that substitutes that obtained from the adoption of dynamical models in model-based strategies. In this context, among most DD2 controllers, a distinction can be made between algorithms that fall into the category

Table 5
Summary review table: DD2 studies.

Ref.	Type	Control			$\mathcal{J}$			Constr. handl.		f_{ex},η know.			RT opt.	Proof		Design compl.	Res. eval.			Wave eval.	
		f_{PTO}	$v_{ref.}$	Par.	$f(E)$	$f(E,\cdot)$	Oth.	y	f_{PTO}	S_η	t	$\mathcal{T}_P$		Conv.	Stab.		L	NL	Ex.	R	I
[146]	DD2			●		●		◆		●			●	●		🟨	●			●	●
[147]	DD2	●				●		◆	◆		●		●	●		🟥	●				●
[148]	DD2			●	●					●			●			🟨	●				●
[149]	DD2			●	●						●					🟨	●		●		●
[150]	DD2			●		●		◆	◆	●			●	●		🟧	●			●	●
[151]	DD2			●		●		◆		●			●	●		🟥		●		●	●
[152]	DD2			●	●					●			●			🟨	●				●
[153]	DD2			●		●		◆	◆	●			●	●		🟥		●		●	●
[154]	DD2			●		●		◆	◆	●			●	●		🟥	●			●	●
[155]	DD2			●		●				●			●	●		🟧		●		●	●
[156]	DD2			●	●					●			●	●		🟧	●	●		●	●
[157]	DD2			●	●						●					🟨			●		●
[158]	DD2			●	●								●	●		🟥	●			●	●
[159]	DD2			●	●			◆					●	●		🟨		●			●
[160]	DD2			●	●					●			●	●		🟨	●			●	●
[161]	DD2			●		●		◆	◆	●	●		●	●		🟧	●			●	●
[162]	DD2	●				●		◆	◆		●		●	●		🟧		●			●
[163]	DD2			●	●					●			●	●		🟧		●		●	
[164]	DD2	●				●		◆	◆		●		●	●		🟧		●	●		●

of reinforcement learning (RL) [144] and those which can be compared to surrogate optimisation [145] processes, applied to the solution of the OCP.

RL algorithms belong to the class of unsupervised learning strategies. They converge to optimal control solutions by learning through punishment and reward, depending on the control actions applied and the associated resulting system performance. Specifically, in RL, an agent, in a certain state s (that describes the conditions of the agent and the surrounding environment), applies an action a. As a consequence of interaction with the environment, the agent moves to a new state s'. Additionally, the action a generates a reward r, related to the function $\mathcal{J}$. The selection of a is modelled as a Markov decision process, based on the value function, which is an estimated value of the total future reward, with the aim to balance exploration of different conditions and actions, and exploitation of the action towards higher rewards. The outcome of this strategy over time is the policy, i.e. the optimal behaviour the control is expected to learn. Several approaches to RL control have been applied in wave energy. In [150,151,155], Q-learning strategies [165] are implemented to guide online the parameters of both passive (in [150,155]), and reactive (in [151]) control laws. Different deep Q-learning strategies (which employ deep ANNs to describe the agent behaviour) are implemented in [147,158,159]. Progressively, [158,159] adopt this strategy to optimise a reactive controller, while the result of the learning process in [147] is the direct optimisation of the control force f_{PTO}. Actor-critic versions of Q-learning have been considered and applied in [162–164]. These two mainly differ in the type of technique employed in the synthesis of the actor-critic strategy. Specifically, [163] employs ANNs to guide a reactive control law, while [162,164] follow a Bayesian approach, based on Gaussian process regression (GPR), to directly optimise the controlled force. It must be highlighted that, in [164], the controller is employed to react to system faults, and has been tested on hardware-in-the-loop facility. Monte Carlo methods [166] have been adopted in the formulation of a Q-learning strategy aimed at optimising a declutching control law in [160], to deal with the variability, due to irregular wave conditions, in computation of the optimal declutching time. Different strategies, such as Q-learning, least-squares policy iteration (LSPI) [167], and state–action–reward–state–action (SARSA) [144], have been compared in [153], to assess their capability to guide a passive controller. A similar least-squares policy iteration approach is implemented in [154], to optimise a reactive control law, taking into account (in a soft manner) eventual constraints. Finally, in [149,157], data taken online from an array of point absorbers is used in a collaborative manner to train an ANN agent, aimed at guiding reactive and latching control laws, respectively.

Surrogate-optimisation-like solutions make use of a metamodel to store information obtained during the learning process. The metamodel is updated with data obtained online, describing the mapping between system inputs (control actions and disturbance) and an estimate of the value that the function to be optimised takes under those conditions. The output estimated by the metamodel is then used as the function to be optimised in the control action computation. In this category, different types of structures can be adopted to build the metamodel. In wave energy, an approach based on ANN training is employed in [146,148,152]. In these studies, the relationship between sea conditions (given by T_e and H_s), and control parameters (stiffness and damping in [146,152] and only damping in [148]), along with the corresponding average absorbed power, is retrieved from data using ANNs. The ANNs are continuously updated and used to select the parameters to be adopted to maximise energy absorption. In [156,161], the same relationship is obtained using GPR, with the only difference given by the output $\mathcal{J}$ which, in [161], is formulated as the performance function for the WEC control competition described in [168]. A summary of DD2 studies can be found in Table 5.

Table 5, with the exception of [147,162,164], indicates that all DD2 strategies aim to optimise a parametrised control law, rather than the control force f_{PTO} directly. This is a consequence of the definition of both $\mathcal{J}$ and the constraints present for specific WEC systems. In fact, DD2 controllers, not having an available model of the system, define $\mathcal{J}$ in an average fashion (e.g. the average value of absorbed power over a certain past interval). The averaging process becomes necessary to reduce of the inherent variability in power measurement induced by the irregularity of waves [57]. The absence of a model precludes the possibility to estimate the wave disturbance at each instant which is alternatively considered via statistical synthetic parameters (i.e. wave elevation spectral information S_η, such as T_e and H_s) obtained from e.g. displacement measurements of specific observation buoys [169] over a specific time window. The unavailability of a model and wave estimates also has an impact on constraint handling. Both these elements are required to 'project' the dynamics of the system into the future, recognising any potential constraint violation. For this reason, in DD2, whenever considered, constraints are almost always incorporated in a soft fashion (with the only notable exception of [159], which proposes a strategy able to bound WEC displacement), and implemented on average as penalising terms in $\mathcal{J}$.

6.3. Data-driven control: Type III

DD3 denotes strategies which synthesise the control system only on the basis only of the information given by data currently produced online, without any model or data storage involved. This category includes MPPT and ESC [128] techniques, typically based on the concept of perturb and observe (P&O) control. Such a process guides the corresponding control action towards optimum performance by adjusting itself only on the basis of the online observation of the effects that a slight perturbation applied to the control law has on the objective function. Such strategies have been successfully applied in the conversion process of other renewable energy sources, such as wind and solar. Comprehensive surveys on MPPT applications for wind and solar can be found in [170], and in [171–173] respectively, while relevant examples of ESC for these renewable energy sources include [174] (wind), and [25] (solar). The success of such approaches in these fields (which share the energy-maximising objective with wave energy), together with the opportunity of having a direct controller which does not employ any model, motivated a number of application studies within WEC control. Preliminary surveys on MPPT and ESC applications in wave energy are presented in [175,176], respectively.

Several application attempts of MPPT control in wave energy have been made. In [177,178], a fixed-step P&O MPPT algorithm, aimed at maximising average absorbed power, is developed, to control the PTO by guiding its load conditions, with performance assessed on a hardware-in-the-loop facility. In [179,180], the results of the application of two MPPT strategies (a fixed-step P&O, and an alternative technique termed cycling MPPT) on a half-scale device (WET-NZ [181]) are presented, in realistic ocean conditions. Similarly, fixed-step P&O algorithms have been implemented for passive control for a gyroscopic WEC in [182], a point absorber in [183], and a duck-like WEC in [184,185]. A latching controller, defining the mass flow rate of a Wells turbine in an OWC, is optimised with a similar P&O strategy in [186]. Definitions of performance functions $\mathcal{J}$ that differ from (the typical) average absorbed power can be found in [186–188]. In particular, in an attempt to reduce the influence of sea-state variability on power absorption, in [186,187], the authors define $\mathcal{J}$ as the mean capture width, instead of the classical average absorbed power (as presented in Eq. (2)). In [188], the effects choosing either mechanical or electrical average power, in a P&O MPPT control, are analysed. Adaptive step size in P&O MPPT algorithms have been adopted in the control of point absorbers, gyroscopic, and pendulum WECs in [189,190], and [191], respectively, in the attempt to improve convergence to optimal conditions. With the same goal, multi-level-step P&O MPPT algorithms have been studied in [192,193]. In [194,195], a P&O with an adaptive perturbation size, based on a hill-climbing algorithm, is employed. Optimisation algorithms have been reformulated to solve the MPPT problem in [196], where a genetic algorithm-like strategy [197] is used to guide a reactive controller, using data from an array of WECs. Finally, in a similar fashion, [198] employs a MPPT approach based on particle swarm optimisation [199], to optimally control a point absorber using a reactive control law.

To the best of our knowledge, the first ESC application in WEC control was presented in [89], where a continuous-time perturbation-based ESC is employed to optimise the power absorption of a point absorber system, following the implementation described in a seminal study [200]. A discrete-time version [201] of this algorithm is adopted in [202], to guide a reactive control law. A comparison study is presented in [203], where five different ESC algorithms are implemented and adopted for the optimisation of both passive and reactive control laws, with application to a submerged point absorber, comparing a continuous-time sliding mode ESC [204,205], a discrete-time relay ESC [206], a discrete-time least-squares ESC [207], a continuous-time self-driving ESC [208], and a continuous-time perturbation-based ESC [200], (indicated in the summary Table 6 as [203]a, [203]b, [203]c, [203]d, and [203]e, respectively). These strategies are compared in different regular and irregular wave conditions, in terms of convergence capabilities and oscillations once the optimal condition is reached. In [209], the same perturbation-based ESC developed in [203] is modified to accommodate soft constraints on f_{PTO} and $\dot{z}$. Finally, in [210,211], an ESC, based on a flower pollination algorithm is implemented to control a Wavestar buoy [212], with a reactive control law.

Table 6 summarises the reviewed studies within this section, showing that the DD3 strategies optimise an (often simple) parametrised control law. This trend, already seen in the DD2 controller class, directly relates to the lack of assumptions made on the system to be controlled (no model), precluding the optimisation of a control force or velocity profile; weaker initial assumptions and available WEC information at the control synthesis stage leading to simpler control laws. A further explanation is given by the need for an averaging process in the evaluation of $\mathcal{J}$, as also observed in DD2 (see the discussion in Section 6.2). Since the behaviour of the controlled process is evaluated in an average fashion, adjustments made to optimise the control action tend to happen at a slower pace than the dynamics characterising the WEC itself, preventing the immediate and direct optimisation of the applied force or velocity.

Regarding $\mathcal{J}$, the same averaging process employed in DD2 is needed to ameliorate the stochastic power conversion introduced by the irregular wave behaviour [57,176]. However, if only pure averaging is applied, the required time window $T_{\mathcal{J}\ eval.}$ can be of the order of hundreds of wave periods [176]. This, together with the need to reduce the sensitivity of $\mathcal{J}$ to diverse sea conditions, led several studies to directly modify the performance function. In [203], prior to averaging, the absorbed power is filtered with a low-pass filter. Then, after the averaging process, a logarithmic compression operation is applied to the obtained function. This reduces $T_{\mathcal{J}\ eval.}$, diminishing the sensitivity of the design parameters to wave conditions. Similarly, in [186,187], the average power is normalised by the energy transport of the incident wave per unit width of wave front, which is a function of the wave elevation spectrum S_η. For ESC, there are additional requirements on $\mathcal{J}$ to guarantee stability [200], and $\mathcal{J}$ must be a convex function of the control law parameters optimised by the ESC [176]. This further limits the type of parameterisation available for the control law which, in most of the reviewed cases, is either simple (two parameter) reactive or passive control.

Finally, Table 6 shows that no online optimisation is required by the various DD3 strategies. Since $\mathcal{J}$ cannot be defined in terms of a model (as done in DD1), or by a storing structure (as in DD2), the solution of the WEC OCP (as defined in Section 3) cannot be optimal. Nonetheless, DD3 strategies are effectively optimisation algorithms applied in real-time to compute the associated control action. Most of these are based on the same working principles as gradient-based solvers, and each action taken corresponds with a solver iteration. This is particularly evident with ESC, whose theoretical principles also have applications in the field of numerical optimisation (see e.g. [213]), or in studies such as [109,198] where control algorithms are directly defined in terms of popular global optimisation solvers.

7. Inter-class comparative analysis

In this section, WEC controllers identified by the classification presented in Section 4 are compared, an initial comparison focussing on the degree to which state-of-the-art research has advanced the different

Table 6
Summary review table: DD3 studies.

Ref.	Type	Control						Constr. handl.		f_{ex},η know.			RT opt.	Proof		Design compl.	Res. eval.			Wave eval.	
		f_{PTO}	v$_{ref.}$	Par.	$f(E)$	$f(E,\cdot)$	Oth.	y	f_{PTO}	S_η	t	$\mathcal{T}_P$		Conv.	Stab.		L	NL	Ex.	R	I
					$\mathcal{J}$																
[177]	DD3			●	●											🟩			●		●
[178]	DD3			●	●											🟩			●		●
[182]	DD3			●	●											🟩	●			●	
[202]	DD3			●	●									●	●	🟨		●		●	●
[89]	DD3			●		●					●					🟨	●				●
[179]	DD3			●	●											🟩			●		●
[180]	DD3			●	●											🟨	●		●		●
	DD3			●	●								●	●	🟩	●	●	●	●	●	
[189]	DD3			●	●											🟩	●				●
[203]a	DD3			●	●									●	●	🟨		●		●	●
[203]b	DD3			●	●									●	●	🟨		●		●	●
[203]c	DD3			●	●									●	●	🟨		●		●	●
[203]d	DD3			●	●									●	●	🟨		●		●	●
[203]e	DD3			●	●									●	●	🟨		●		●	●
[209]	DD3			●		●		◆	◆					●	●	🟨		●		●	
[196]	DD3			●	●					●				●		🟨	●				●
[190]	DD3			●	●											🟩			●	●	●
[210]	DD3			●		●										🟨	●				●
[192]	DD3			●	●											🟧	●			●	
[191]	DD3			●	●										●	🟩	●			●	
[194]	DD3			●	●											🟨			●	●	
[195]	DD3			●	●										●	🟧	●			●	
[193]	DD3			●	●									●		🟨		●		●	●
[211]	DD3			●	●											🟨	●		●		●
[184]	DD3			●	●											🟩		●		●	
[188]	DD3			●			●									🟩		●	●	●	●
[198]	DD3			●	●					●				●		🟨	●				●
[187]	DD3			●		●				●				●	●	🟩		●			●
[186]	DD3			●		●				●						🟩		●			●
[183]	DD3			●	●											🟩	●			●	
[185]	DD3			●	●											🟩		●		●	●

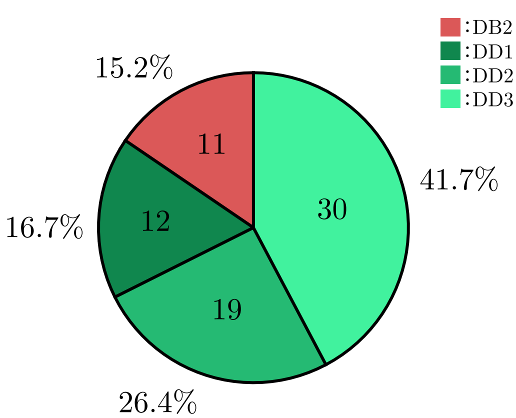

Fig. 4. Inter-class comparative analysis: number of reviewed studies per control type.

types of strategies. Fig. 4 illustrates the number of studies reviewed for each of the control types (DB1 is excluded here since, as already mentioned in Section 5.1, all the model-based control strategies which employ a model obtained following one of the data-based procedures in Table 1 fall in this category).

Note that the greatest percentage of reviewed studies relates to DD3 controllers (41.7%), demonstrating the popularity that MPPT strategies have in the field of electrical engineering in general, and the simplicity of implementation that characterises most algorithms belonging to this category. It should be also highlighted that an increasing interest in learning-based control strategies observed in other application fields [214] is also witnessed here, as per the number of reviewed studies from DD2 (26.4%).

A second important comparison relates to the capabilities of WEC controllers in handling constraints, specifically considering the way in which constraints are handled (i.e. not included, soft formulation, or hard formulation), and in terms of the constrained variables (i.e. y and/or f_{PTO}). The results of this analysis, from the data in Tables 3 to 7, are shown in Fig. 5. Most DD1 strategies consider constraints (with the exception of [137]), and this category is also able to implement hard constraints. Similarly, the availability of appropriate data at the control synthesis stage facilitates constraint handling in the DB2 controllers. In contrast, the opposite is true of DD2 and DD3 controllers. For DD2, only roughly half of the studies consider constraints during the control synthesis procedure, typically using soft constraints. For DD3, this trend is even more evident, since, apart from [209], none of the strategies consider constraints. The difficulty of handling constraints in the case of DD2 and DD3, as already analysed in Sections 6.2 and 6.3, can be explained by the averaging process that these strategies adopt to deal with the stochastic wave disturbance. Since all the information exploited by such strategies is averaged, handling constraints in real-time becomes a more difficult task to be accomplished.

Another comparison relates to the availability of theoretical guarantees with respect to convergence and stability, which are of fundamental importance. Here, we provide information on the availability of such guarantees, demonstrated either numerically or analytically, reported

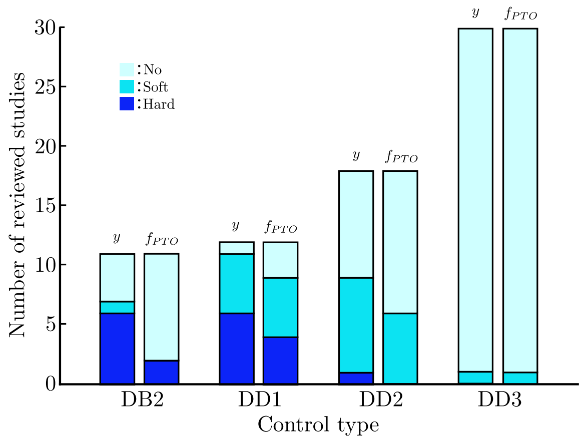

Fig. 5. Inter-class comparative analysis: constraint handling capabilities.

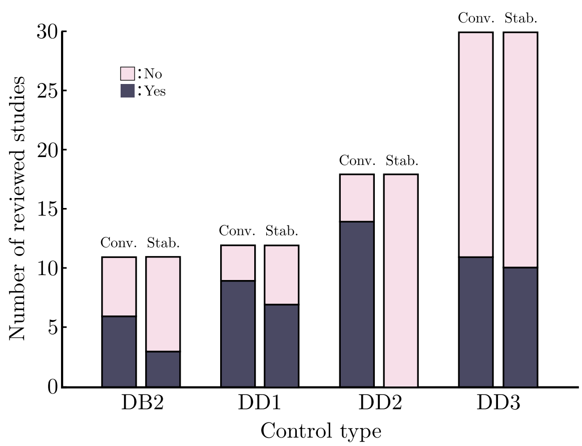

Fig. 6. Inter-class comparative analysis: convergence and stability proves.

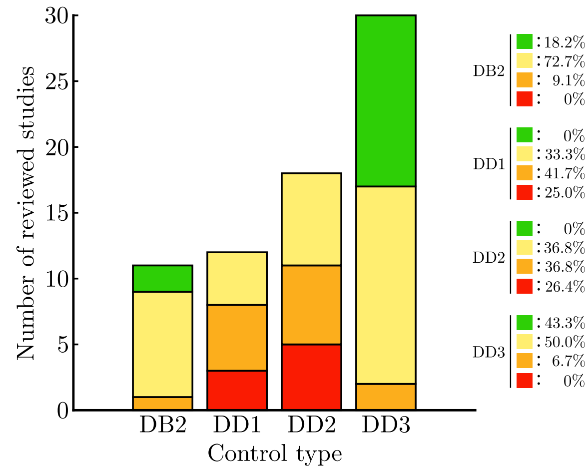

Fig. 7. Inter-class comparative analysis: number of design parameters per control type.

in Tables 3 to 7, and summarised in Fig. 6. Clearly, the DD1 category is, on average, most populated with stability and convergence results. This can be explained by the adoption of well-established model-based control techniques, already analysed theoretically and applied to a vast number of processes (e.g. standard MPC). Fig. 6 also highlights the lack of stability proofs for DD2 controllers, typically rely on ANNs in the learning process, with the stability of ANN-based controllers still a relatively open question in control theory [215–217]. The presence of several stability and convergence proofs in DD3 (which enjoys even less information on the controlled system than DD2) can be explained by the percentage of DD3 studies belonging to the ESC category, where proofs of stability and convergence have been an active topic of interest in recent decades, culminating in the seminal study of Krstić in [200]. The stability of classical ESC scheme is proven for a general class of nonlinear systems, using tools from averaging and singular perturbation analysis. Some MPPT P&O approaches [187,191,195] also provide some stability results, articulating the relationship between the size and frequency of the perturbation and closed-loop stability [218,219].

As reported in Tables 3 to 7, and summarised in Fig. 7, each reviewed study has been classified on the basis of the parameters required to be tuned by the designer. Four ranges (reported in the legend provided in Table 2) are identified. Fig. 7 (where also the relative percentages are reported) shows the strong correlation between the amount or retained system information and the number of parameters that require tuning. The most frequent number of free parameters to be designed in DD1 controllers is 9–12 (41.7%), while in DB2 and DD2 this number decreases to 5–8 (72.7% and 36.8%). In DD3, the most frequent range is also 5–8 (50.0%), but closely followed by 1–4 (43.3%). This trend reflects the greater design freedom when prior information on the systems (given by a model, or by stored data) are available, translating into the possibility of developing more complex control laws, requiring more design parameters. However, a greater number of design parameters *does not necessarily mean that the tuning stage is more complex*. As observed in the reviewed studies, when less parameters are considered, these are typically more sensitive to the wave conditions in which the WEC has to be controlled, making the control design, and hence the choice of parameters, potentially non-trivial.

7.1. On the relation between data and optimisation-based WEC control

Attention is now devoted to optimisation-based control strategies, excluding DB2 and DD3, given their lack of online optimisation activity (see Tables 3 and 6) once the control strategy is implemented (one of the main aims of DB2 is to reduce the computational effort required online while, as mentioned in Section 6.3, DD3 techniques are, in essence, optimisation solvers). As also analysed in [220], optimisation-based controllers, which make use of data, can be divided in data-driven learning-based control (belonging to DD2), and data-driven adaptive control (subset of DD1). The way in which data and the optimisation process interact with the rest of the elements in the control loop is different, as graphically explained, and compared with classical optimal model-based control, in Fig. 8, show that online data (green lines) directly modify the optimisation problem in DD2. In DD1, these data can potentially affect the model of the system, which can also be constructed/computed from an offline dataset (red lines). The presence of a model indirectly facilitates the wave estimation process (as in model-based WEC control).

Regarding the goal of the optimisation process, similarly to model-based optimal WEC control, DD1 optimisation maximises $\mathcal{J}$. Apart from penalisation of constraint violations, the sole goal is energy-maximisation. In DD2, the presence of learning affects the optimisation, balancing the activities of exploration and exploitation. Depending on the type of DD2 controller (i.e. RL or surrogate optimisation-like), and the structure used to memorise past experiences, the learning strategy interacts differently with the optimisation process. Other than ANN-based surrogate optimisation-like algorithms, which separately define the learning strategy, all other learning algorithms (GPR-based optimisation-like and reinforcement learning) incorporate management of the learning strategy within the optimisation process (and objective function). Consequently, the optimisation goal is not only energy maximisation, but also optimisation of the learning process

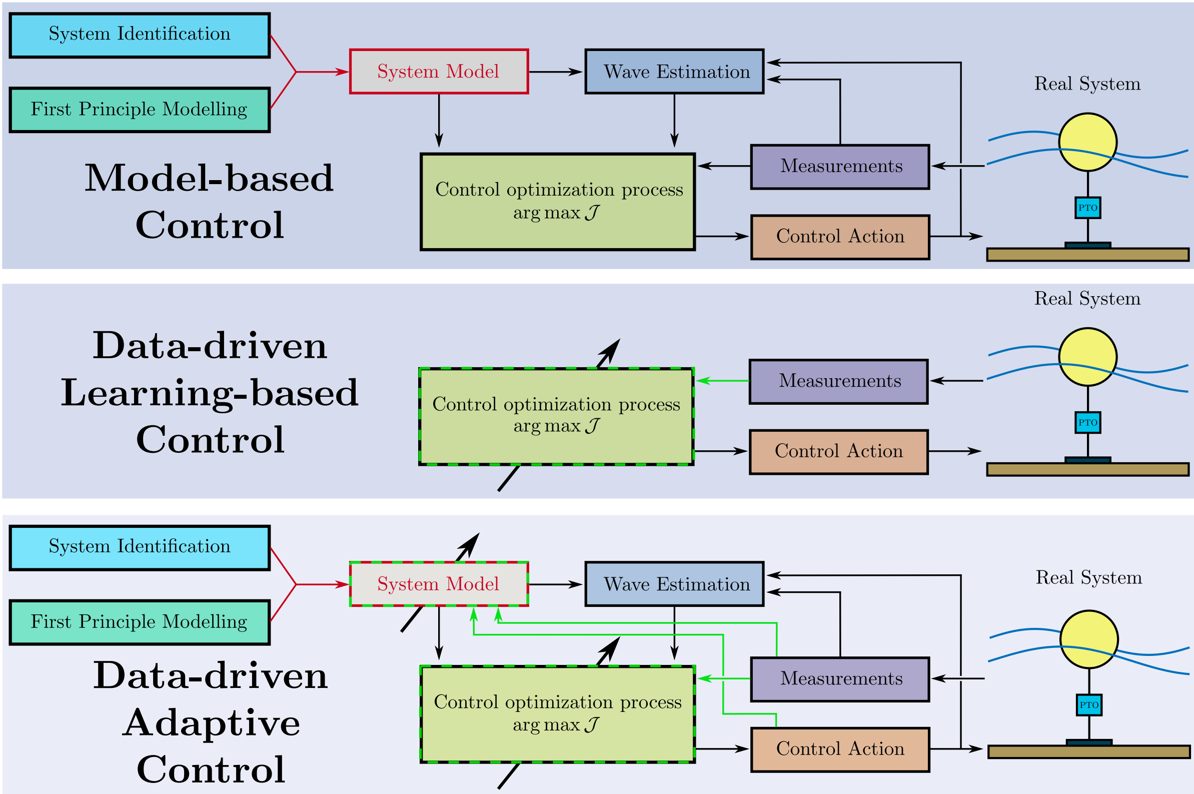

Fig. 8. Optimisation-based control working principles: the differences between model-based and data-driven approaches (adapted from [220]). Different line colours emphasise the different data flows and the elements influenced by them (green lines for online data, red lines for offline data).

7.2. Perspectives and future directions

WEC control based on, or driven by, data is a relatively young, but promising, field of research within the wave energy community, with a diversity of proposals reported. Each of the identified control categories within this paper has its own strengths and limitations and, as a result, there is no clear 'winner'. Specifically, further research on DB1 control strategies should focus on developing models, based on data, that are well-validated even in controlled conditions to circumvent the WEC modelling paradox [12]. The availability of suitable experimental data from tests should act as a key contributing factor in this direction. Regarding DB2, these solutions have potential when considered together with high-fidelity simulation environments, both in solving the problems related to unmodelled hydrodynamics in control-oriented models, and the relatively high computational effort required by optimal control strategies. In this context, high-fidelity hydrodynamic solvers [221] based on computational fluid dynamics (CFD), or smooth particle hydrodynamics (SPH), can provide valuable simulated data for the synthesis of DB2 controllers. Moreover, since most DB2 strategies employ ANNs in their synthesis procedure, stability proofs are also a topic to be further investigated, to guarantee reliable utilisation of these strategies in realistic WEC systems. Concerning DD1 controllers, we believe that the combination of well-established model-based control algorithms with an online dataset make this category appealing, in terms of applicability in real world scenarios. However, the computational effort required by the multiple optimisation loops that characterise this category, not only to compute the optimal control action, but to adapt the model employed in online synthesis can preclude effective real-time implementation. In relation to DD2 strategies, we recognise the potential that a learning process can have in controlling devices on which standard control-oriented modelling assumptions can be limiting. In particular, when highly nonlinear effects are dominant, learning control can provide a good alternative, also in terms of adaptability, if the device operates for long periods of time. However, for the sake of completeness, we also witness a lack of stability proofs in the development and application of DD2 strategies for wave energy systems that, together with the common averaging approach to the definition of $\mathcal{J}$ and associated constraint handling, leave room for further research. Finally, regarding DD3, the avoidance of the adoption of either model or storage structures seems attractive for the WEC control problem. However, most of these studies are based upon simple control laws, which ultimately limit the capability of DD3 strategies. Moreover, among the considered studies, there is a consistent lack of constraint handling ability, mostly due to the averaging approach which characterises the DD2 and DD3 categories. This topic is, hence, still an open point, worthy of further investigation.

8. Conclusions

This study provides a critical overview of the different control strategies applied to wave energy systems which exploit information coming from data. This research field is rapidly evolving, and it is expected to grow significantly over the next decade. A precise definition of data-based and data-driven control of wave energy systems is offered and, on the basis of that, a classification of state-of-the-art studies on WEC control employing data is identified. Five distinct categories are formulated, detailing their working principles, and the specific role of data in the control synthesis. In particular, this work analyses each of the considered studies in terms of type of control law, constraint handling capability, performance function adopted, convergence and stability proofs, and available/utilised information on the wave disturbance. A critical comparison between the different categories is provided, highlighting issues and limitations, in the attempt to provide the WEC control designer with a general and fair overview of the pros and cons of each approach. With the current state-of-the-art, the adoption of data is still not able to provide an 'ultimate' solution to the

Table 7
Summary review table: total table comparison.

Ref.	Type	Control			$\mathcal{J}$			Constr. handl.		f_{ex},η know.			RT opt.	Proof		Design compl.	WEC type
		f_{PTO}	$v_{ref.}$	Par.	$f(E)$	$f(E,\cdot)$	Oth.	y	f_{PTO}	S_η	t	T_P		Conv.	Stab.		
[109]	DB2	●				●			◆		●					yellow	PA
[110]	DB2		●		●			◆		●	●				●	yellow	PA
[111]	DB2		●		●			◆								yellow	OWC
[63]	DB2		●				●	◆		●						green	OWC
[112]	DB2	●				●		◆						●	●	yellow	OWC
[113]	DB2			●	●						●			●		yellow	PA
[114]	DB2			●	●									●		green	PA
[115]	DB2			●		●								●		yellow	Att.
[116]	DB2		●				●	◆						●		yellow	OWC
[117]	DB2		●				●	◆		●						yellow	OWC
[118]	DB2	●				●		◇	◆		●	●		●	●	orange	PA
[130]	DD1	●				●		◇	◇		●	●	●	●	●	orange	PA
[131]	DD1	●				●		◆	◆		●	●	●	●	●	orange	PA
[132]	DD1		●				●	◆			●	●	●	●	●	yellow	PA
[133]	DD1		●				●	◆			●	●	●	●	●	red	PA
[134]	DD1			●	●			◇	◇		●	●	●			orange	PA
[135]	DD1		●		●			◆	◆		●	●	●	●		yellow	PA
[136]	DD1		●		●			◆	◆		●	●	●	●		yellow	PA
[137]	DD1	●					●				●	●				yellow	PA
[138]	DD1	●				●		◇	◇		●			●	●	orange	PA
[139]	DD1	●				●		◇	◇		●			●	●	red	PA
[140]	DD1	●				●		◇	◇		●			●	●	red	PA
[141]	DD1	●			●			◆	◆		●	●	●			orange	PA
[146]	DD2			●		●		◇		●			●	●		yellow	PA
[147]	DD2	●				●		◇	◇		●		●	●		red	PA
[148]	DD2			●	●					●			●			yellow	PA
[149]	DD2			●	●						●					yellow	PA
[150]	DD2			●		●		◇	◇	●			●	●		orange	PA
[151]	DD2			●		●		◇		●			●	●		red	PA
[152]	DD2			●	●					●			●			yellow	PA
[153]	DD2			●		●		◇	◇	●			●	●		red	PA
[154]	DD2			●		●		◇	◇	●			●	●		red	PA
[155]	DD2			●		●				●			●	●		orange	PA
[156]	DD2			●	●					●			●	●		orange	PA
[157]	DD2			●	●						●					yellow	PA
[158]	DD2			●	●								●	●		red	PA
[159]	DD2			●	●			◆					●	●		yellow	PA
[160]	DD2			●	●					●			●	●		yellow	PA
[161]	DD2			●		●		◇	◇	●	●		●	●		orange	PA
[162]	DD2	●				●		◇	◇		●		●	●		orange	PA
[163]	DD2			●	●					●			●	●		orange	PA
[164]	DD2	●				●		◇	◇		●		●	●		orange	PA
[177]	DD3			●	●											green	PA
[178]	DD3			●	●											green	PA
[182]	DD3			●	●											green	PA
[202]	DD3			●	●									●	●	yellow	PA
[89]	DD3			●		●					●					yellow	PA
[179]	DD3			●	●											green	PA
[180]	DD3			●	●											yellow	PA
[189]	DD3			●	●											green	PA
[203]	DD3			●	●									●	●	yellow	PA
[209]	DD3			●		●		◇	◇					●	●	yellow	PA
[196]	DD3			●	●					●				●		yellow	PA
[190]	DD3			●	●											green	PA
[210]	DD3			●		●										yellow	PA
[192]	DD3			●	●											orange	PA
[191]	DD3			●	●										●	green	Ter.
[194]	DD3			●	●											yellow	PA
[195]	DD3			●	●										●	orange	PA
[193]	DD3			●	●									●		yellow	PA
[211]	DD3			●	●											yellow	PA
[184]	DD3			●	●											green	Ter.
[188]	DD3			●			●									green	PA
[198]	DD3			●	●					●				●		yellow	PA
[187]	DD3			●		●				●				●	●	green	PA
[186]	DD3			●		●				●						green	OWC
[183]	DD3			●	●											green	PA
[185]	DD3			●	●											green	Ter.

WEC control problem, although each of the analysed approaches can represent a viable alternative to classical model-based strategies under the right circumstances, and specific further development. Finally, considerations on future directions that, from the authors' perspective, research on data-based and data-driven control should pursue, are formulated, in an attempt to provide guidance and support in the pathway towards effective implementation of these techniques in the field of ocean wave energy absorption.

CRediT authorship contribution statement

Edoardo Pasta: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Nicolás Faedo:** Conceptualization, Formal analysis, Writing – review & editing, Supervision. **Giuliana Mattiazzo:** Resources, Project administration, Funding acquisition. **John V. Ringwood:** Conceptualization, Formal analysis, Writing – review & editing, Supervision, Resources, Project administration.

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.

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Appendix. Total table comparison

An additional table, summarising all the reviewed studies, is reported here, together with type of WEC on which the proposed control strategies have been applied (Table 7). For a summary of adopted terminology, and symbols, the reader is referred to Table 2.

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Edoardo Pasta was born in Turin, Italy in 1996. He received the B.Sc. degree in Mechanical Engineering and the M.Sc. degree in Mechatronic Engineering from Politecnico di Torino, Turin, Italy, in 2018 and 2020, respectively. He is currently pursuing the Ph.D. degree, with a focus on optimal control and modelling of wave energy converters, with Marine Offshore Renewable Energy Lab, Politecnico di Torino, Turin, Italy. In 2020, he was Visiting Researcher with the Computational Fluid Dynamics and Flow Physics Laboratory, San Diego State University, San Diego (CA), U.S. Between 2021 and 2022, he joined the Centre for Ocean Energy Research at Maynooth University, Ireland, as a Visiting Researcher. His current research interests include optimal control and modelling of wave energy systems, with a particular focus on data-based and data-driven techniques. In 2022, he was recipient of the 2022 IFAC CAMS Best Paper Award.

Nicolás E. Faedo was born in Buenos Aires, Argentina, in 1991. He received a degree in automation and control engineering from the National University of Quilmes, Buenos Aires, Argentina, and the Ph.D. degree in electronic engineering from the Centre for Ocean Energy Research Group, Maynooth University, Kildare, Ireland, in 2015 and 2020, respectively, with a focus on optimal control and model reduction for wave energy converters from a system-theoretic perspective. In 2017, he joined the Centre for Ocean Energy Research Group, Maynooth University. In 2018, he was a Visiting Researcher multiple times with the Control and Power Group, Imperial College London, London, U.K. He is currently a Postdoctoral with the Department of Mechanical and Aerospace Engineering, Politecnico di Torino, Turin, Italy. His current research interests include nonlinear optimal control theory and data-driven model reduction with special emphasis in applications involving renewable energy systems. He was the recipient of the 2019 ISOPE Best Student Paper Award and the Exxonmobile Prize, finalist for the 2018 IFAC CAMS Young Author Award, and has been selected as an Outstanding Reviewer of the IEEE Transactions on Sustainable Energy, 2020. He was also the recipient of a Marie Sklodowska-Curie Actions Individual Fellowship (MSCA-IF 2020).

Giuliana Mattiazzo received the M.Sc. degree in aerospace engineering and the Ph.D. degree in applied mechanics from the Politecnico di Torino, Turin, Italy in 1991 and 1994, respectively. She is currently Full Professor with the Department of Mechanical and Aerospace Engineering, Politecnico di Torino, where she is also Vice Rector for Technology Transfer, and Director of the Marine Offshore Renewable Energy Lab. Her research interests include renewable energy applications, with particular focus on the development of wave energy converters, floating offshore wind plants, and decarbonisation strategies for local energy communities.

John V. Ringwood received the Diploma degree in electrical engineering from the Dublin Institute of Technology, Dublin, Ireland, in 1981, and the Ph.D. degree in control systems from the University of Strathclyde, Glasgow, U.K., in 1985. He is currently a Professor in electronic engineering with Maynooth University, Ireland, where he is also the Director of the Centre for Ocean Energy Research. He is also a Chartered Engineer and a fellow of Engineers Ireland. His current research interests include time-series modelling, wave energy, and biomedical engineering. He serves on the editorial boards for the Journal of Ocean Engineering and Marine Energy, IEEE Transactions on Sustainable Energy, and IET Renewable Power Generation.