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Review article

Fault diagnosis and fault-tolerant control in wave energy: A perspective

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ABSTRACT

In the decarbonisation path, wave energy systems are gaining attention as a key technology in the renewable energy mix. An essential step towards their effective development is constituted by energy-maximising, optimal control algorithms, which in wave energy systems can maximise energy extraction while respecting system physical constraints. Current strategies rely on mathematical models describing, in a parsimonious yet sufficiently exhaustive fashion, the device dynamics. Notwithstanding, wave energy converters operate in severe environments where extreme wave events and sea corrosion can lead to malfunctions, compromising their reliability. As a damage consequence, the system dynamics can change, entailing structural ambiguity in the nominal model. This uncertainty significantly degrades optimal control performance, potentially compromising the system's health and leading to expensive maintenance costs. Fault diagnosis and fault-tolerant control algorithms are designed to identify and accommodate eventual faults in dynamic systems. As such, they are powerful tools for implementing wave energy resilience features, thus minimising idle device time and extra maintenance operations. This work presents a critical analysis of the status of fault diagnosis and fault-tolerant control in wave energy, starting from parallelism with the sister wind energy field, for which they are substantially more mature. Such tools are put in the wave energy-maximising context, presenting a study of the weak and strong points in the current literature, while proposing potential solutions for the identified pitfalls, and highlighting what is missing to pin fault diagnosis and fault-tolerant control as a silver bullet for improved reliability within the wave energy control field.

1. Introduction

The concern about climate change, is pushing the scientific community to search for alternative energy sources [1]. Fossil-based power production systems are responsible for CO_2 emissions, representing a trigger in the heating phenomenon. Renewable systems, such as solar, wind and wave energy, play a crucial role towards decarbonisation, constituting a strategic asset in the energy mix of present and future years. Nonetheless, contrarily to solar panels or wind turbines, wave energy is still an immature field, with research fundamentally pushing towards economic viability [2–5]. A key element is the development of optimal control (OC) strategies which, based on a physical device mathematical model, maximise power extraction from wave energy converter systems (WECs), while respecting technical constraints [6–8]. Nonetheless, OC fail when the system behaviour differs significantly from the mathematical model. If under nominal conditions, such discrepancy can be controlled with parsimonious, but still representative enough, modelling techniques, the marine harmful environment entails a high risk of damaging the WEC system, *e.g.* with water corrosion and/or extreme wave scenarios [9]. Faults can lead to a considerable model-system discrepancy, implying severe OC performance degradation, or the worst scenario, compromising the system reliability.

Consequently, it is required to plan maintenance operations when damage occurs in the system. Following the cost of energy reduction paradigm, note that repairing off-shore devices can be expensive, and planning frequent maintenance actions can overcome the economic advantage of energy-maximising OC [10]. A valid alternative is to prevent the damages while still maximising power production in case of non-critical damages, enhancing reliability and energy cost. In fact, the WEC system can often incur minor damages, such as a sensor drift or a friction increase in the actuator systems, which do not fully compromise its functionality per-se. Notwithstanding, the OC logic, which is designed on the basis of the faultless system's dynamics, may incur suboptimal, or even dangerous solutions, compromising the health of the WEC in these faulty scenarios. In this context, a routine is required to correct the control action provided to the system, allowing it to continue the energy-extraction operations while ensuring reliability under OC. In this way, costly maintenance operations, connected with

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the intricate logistics for reaching off-shore spots, that which would have been mandatory in case of system shutdown, can be avoided altogether.

Fault diagnosis and isolation (FDI) algorithms, in combination with fault-tolerant control (FTC) techniques [11] appear to be a valid solution. Such strategies are designed to keep the controlled system working correctly, even under faults. In particular, FDI routines are designed to detect, isolate and (eventually) estimate any associated fault in the system, while FTC focuses on accommodating/reconfiguring the control strategy to minimise loss of performance, despite the damage occurrence. Numerous industrial applications, *e.g.* automotive, aeronautics, or nuclear energy, for which the loss of capability to accomplish the system's primary tasks entails severe consequences, employee FDI and FTC systems [12]. Within the renewable energy field, wind turbines experimented within the last decades a strong request for reliability, consequently FDI/FTC emerged as promising solutions for such a demand [13–15].

Notwithstanding, the reliability feature is certainly not the case in wave energy, where FDI and FTC are still underdeveloped technologies. This aspect can be partially attributed to the WEC control problem nature, which departs from traditional regulation/tracking objectives, such as those pursued in sister renewables (*e.g* wind energy), as discussed in Section 2.

Following such discussion, it is worth to notice that an in-depth and critical discussion of FDI and FTC within the field of wave energy conversion, which has the potential of identifying key points for effective further development, is missing in the current literature. We do note that, although, an effort in this direction has been recently performed in [16], which provides an overview of different FDI and FTC techniques and their application in the field. Nonetheless, while [16] effectively lists a subset of studies considering FDI/FTC for different wave energy concepts, these are not classified and contextualised in their corresponding theoretical frameworks (*i.e.* from a control theory perspective) but rather simply by the underlying WEC concept, nor compared with sister renewable energy applications, where FDI/FTC have been already successful. Motivated by the lack of a systematic and comprehensive critical review of FDI and FTC within the wave energy conversion field, and with the intention of providing guidelines and new possible directions for successfully implementing fault-tolerant strategies within the WEC field, this study describes the relevant features of wave FDI/FTC algorithms in the literature, and subsequently critically analyses the possibilities and pitfalls which each strategy brings to the field, study by study, in dedicated sections. Such features are then compared with some of the most relevant studies in wind energy, highlighting similarities, differences, and the motivations hindering the development of fault-tolerant techniques in WEC systems. A final discussion, as part of the employed analysis methodology, points out the current issues, possible solutions, and what is missing to unlock the FDI/FTC potential in the wave energy field.

The remainder of this work is organised as follows. Section 2 introduces the basics behind the wave energy OC problem, while showing relevant model-based techniques in the field. Section 3 presents the general definitions of FDI and FTC, and concisely describes the major applications in wind energy systems. Sections 4 and 5 present a review of the studies of wave FDI and FTC, respectively, focusing on their possibilities and pitfalls. Finally, in Section 6, are given the possible solutions to the highlighted issues, and what is missing to make wave FDI/FTC a competitive technology, contributing to improving the reliability of WEC systems.

2. The wave energy optimal control problem

WEC control aims to maximise the power extracted from the wave-induced motion, *i.e.* is an energy-maximisation criterion. From now on, without any loss of generality, the authors refer to the WEC control problem in a single degree-of-freedom (DoF) case, for the sake of simplicity of notation. The results discussed in the following can be extended to multi-DoF devices (see *e.g.* [17]). The energy-maximisation criterion is expressed in the optimal control (OC) problem with an objective function:

$$J = \frac{1}{T}\int_0^T u(t)\dot{z}(t)\mathrm{d}t, \tag{1}$$

which indicates the extracted energy over the time window T. In (1), the terms u and $\dot{z}$ represent the control action, exerted via the power take-off system (PTO), and the time derivative of the considered DoF displacement, *i.e.* the velocity, respectively, while t is the time. The main goal of OC is to design u for maximising the objective function in (1). Due to WECs' mechanical or electrical limitations, the unconstrained solution of (1) cannot be implemented in practice. This aspect is related to unrealistic values assumed by displacement z, velocity $\dot{z}$, and the control action magnitude u, under energy-maximising conditions. Consequently, it is necessary to define such limitations within the OC framework, to enable the problem solution to cope simultaneously with the energy maximisation, and the imposed constraints. A common procedure is to write such conditions as a set of constraints, *i.e.*

$$C : \left\{|z| \le z_{max}, |\dot{z}| \le \dot{z}_{max}, |u| \le u_{max}\right\}, \tag{2}$$

where $\left\{z_{max}, \dot{z}_{max}, u_{max}\right\} \subset \mathbb{R}^+$ represent maximum admissible values for each associated variable in (2).

Within the WEC control literature, it is common practice to represent the system dynamics as a set of continuous time, finite-dimensional, nonlinear dynamical equations:

$$\Sigma : \begin{cases} \dot{x} = g(x, u, w), & x(0) = x_0 \\ y = h(x), \end{cases} \tag{3}$$

where x is the state vector, x_0 is the initial state, w is an unknown, uncontrollable input (*i.e.* the wave excitation force), $\{g, h\}$ are two sufficiently smooth nonlinear mappings. Note that the output function y in (3) is typically set to $y = \dot{z}$.

Remark 1. The state-transition map g in (3) is obtained by exploiting potential flow theory [18]. This allows for constructing a parametric model of the WEC system, representing the primary dynamics with a moderate computational burden.

The OC problem comprises the dynamical WEC representation in (3), the constraint set in (2), and the objective function in (1), as

$$\begin{aligned} & u_{opt} = \arg\max_u J, \\ & \quad \text{s.t.} \\ & \quad \text{WEC dynamics in (3)}, \\ & \quad \text{Constraints in (2)}. \end{aligned} \tag{4}$$

Remark 2. Problem (4) solution depends on w, *i.e.* implies that current and future knowledge of the wave excitation force over the time horizon T is available to reach the corresponding optimum. Such prediction is not available in practice, and the OC problem for wave energy converters is anti-causal (see [19]). Additionally, a critical aspect resides in the impossibility of measuring the wave excitation force with physical sensors (*e.g.* pressure probes) [20].

Following the discussion in Remark 2, a well-established procedure is approximating the problem (4) solution by replacing the wave excitation force measure with its estimate, and future knowledge of w with a time-series forecast (generated by prediction algorithms). The reader is referred to [21] for additional details.

2.1. On the state-of-the-art of WEC control algorithms

This part is not intended to provide an exhaustive review of WEC OC techniques, but just an appraisal of them, to allow the reader a more immediate reference for the work core body discussion, especially in Sections 4 and 5. The reader is referred to other WEC OC literature reviews, such as [22,23], for a deeper discussion of the topic.

Model-based control solutions to problem (4) can be broadly divided into three sub-categories: optimal controllers, impedance-matching-based controllers, and robust control strategies.

OC techniques aim at providing a solution of (4), which is an infinite-dimensional optimisation problem. The vast majority of the available WEC strategies discretise system input and state variables, to transcribe (4) into a computationally tractable finite-dimensional nonlinear program [24]. This approach is called direct optimal control, and its primary application to WEC systems is model predictive control (MPC) [25]. Other techniques are based on spectral/pseudospectral control [26], differential flatness [27], and moment-based control [21].

Some studies solve problem (4) with an indirect optimal control approach, where the so-called dual problem associated with (4) is discretised accordingly (see [24]). In particular, indirect optimal control leverages the Pontryagin maximum principle (see *e.g.* [28]). The advantage of an indirect approach is the employment of lower sampling rates, while retaining solution optimality. However, the fact that the associated problem is not trivial to solve requires knowledge of the problem structure for retrieving the optimal solution numerically, reducing their appeal to direct formulations.

Remark 3. Direct/indirect control methods can include state and input constraints within the optimisation problem, which appears promising for WEC OC requirements.

OC real-time implementation can be computationally expensive, and depends on factors such as the problem dimension and the discretisation rate. Such a computational cost must be balanced regarding hardware complexity, and sometimes can compromise real-time feasibility [29]. Hence, some strategies 'divide' the control solution into a composite loop, where optimal trajectory is obtained within a coarser sampling time, allowing for a sufficiently large window for computation. Simultaneously, a secondary controller tracks the trajectories in real-time [30]. In other words, the inner tracking controller does not solve problem (4), but only performs the computational less demanding unconstrained trajectory following.

To reduce the computational complexity of OC techniques, impedance-matching (IM) strategies are based on the principle of impedance matching for maximum power transfer in electrical circuits [31]. IM aims at finding a static, (often) linear time-invariant (LTI), control law derived from such a maximum power transmission principle [32,33]. Nonetheless, as discussed in Section 2, the IM optimal condition is also non-causal, *i.e.* the controller depends on instantaneous and future knowledge of the wave excitation force. A standard solution is to approximate the controller structure to maximise energy extraction on the correspondence of any operating sea-state significant energetic/spectral peak period/frequency. This technique provides an intuitive framework for effective controller design, which can be easily implemented in a real-time system. Nonetheless, IM control does not entail stability guarantees or state/input constraint handling structures. Such properties are implemented with additional routines (as in [34]), therefore changing the (approximated) optimality condition.

The hydrodynamic WEC modelling uncertainties [35] motivate the consideration of (4) under a robust point of view, for developing power-maximising strategies insensitive to modelling errors. The issue in robust control is related to the uncertainty. Defining 'large' uncertainty levels, implies a conservative control synthesis, *i.e.* the controller performance deviates from the nominal case. The problem can be solved by precisely characterising the model uncertainty. Nonetheless, the assumptions within (control-oriented) hydrodynamic modelling involve a large degree of uncertainty, and hence precise bounds are unavailable. Although, in WEC control, such conservationism can imply a significant power production degradation, and thus energy maximisation principle is far from being respected. Some applications of WEC robust control can be found in [36–38].

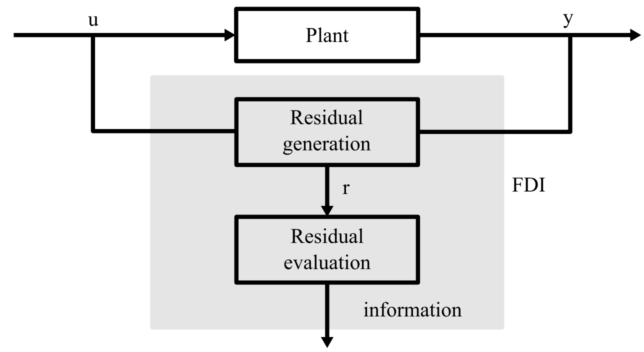

Fig. 1. Schematic representation of an FDI system.

3. Fault tolerant control problem

Over the years, control systems coping with faults gained increasing attention. These are called fault tolerant control (FTC) algorithms [11]. The fault detection, isolation and identification (FDI) module [39], supervises, in real-time, the system dynamics and provides the damage information. Renewable energy fields, such as wind [40], exploited FTC techniques to increase their reliability, lowering the associated levelised cost of energy. Given that wind energy presents similarities with wave energy, and that wind turbine development is at a more mature point to WECs, the FTC/FDI strategies adopted in wind energy are briefly described in the following. This section presents the FDI and FTC problems, alongside the main features of wind power FDI/FTC systems.

3.1. Fault detection, isolation and identification (FDI)

Model-based FDI consists in detecting, isolating and characterising faults happening in a system, given the measurements and mathematical models. A formal definition is given following the behavioural paradigm [11].

Definition 1 (*FDI Problem: Behavioural Formulation*)**.** Given a faultless $\mathcal{B}_0$ and a faulty $\mathcal{B}_f$ plant behaviour, and an input–output pair (U, Y), if

$$(U, Y) \notin \mathcal{B}_0, \quad \wedge \quad (U, Y) \in \mathcal{B}_f, \tag{5}$$

find the fault f.

As described in [11,39], a classification of the different tasks executed in a generic FDI system is:

- Fault diagnosis: decide if the system behaviour is consistent with the nominal (faultless) working condition.
- Fault isolation: determine the nature of the fault, *e.g.* if the faulty component is a sensor, an actuator, a model parameter, etc.
- Fault identification/estimation: estimate accurately the fault signal in time.

Since differential equations can represent a large subset of dynamical systems, it is convenient to define the fault tolerant control problem using standard tools employed in classical system dynamics theory. A general scheme for FDI is given in Fig. 1.

Let us consider a generic deterministic nonlinear dynamical system, represented as in (3). In the case of fault, the dynamics in (3) can be expressed as

$$\Sigma_f : \begin{cases} \dot{x}_f = g_f(x_f, u_f, w, f), \quad x_f(0) = x_{f,0} \\ y_f = h_f(x_f, f), \end{cases} \tag{6}$$

where f is the fault in the plant. A generic fault f, affecting only the control system, is called an actuator fault. If the fault changes only measurements, a sensor fault is tanking place. If a variation of process parameters occurs, a plant fault is diagnosed.

An analytical redundancy relation occurs when a constraint set is redundant compared to the measurements, *i.e.* a variable can be obtained with different paths [11] (*e.g.* multiple sensors measuring the same quantity, dynamical observers, parity relations — see Section 3.1 for further details). Fig. 1 synthetically presents the main FDI architecture, in which Analytical redundancy relations constitute the primary tool to design the residual vectors, which are the quantities carrying the system fault information.

Definition 2 (*Deterministic Residual Generation*)**.** Given system in (6), find a residual vector r which depends on f and has the following properties:

$$\begin{cases} r = 0, & \iff \quad f = 0 \\ r \neq 0, & \iff \quad f \neq 0 \end{cases} \tag{7}$$

Following Definition 2, each residual must be 0 when the associated fault is present, while being insensitive to other faults. Residual vectors are derived from available ARRs by comparing the actual system behaviour with (8).

Each fault structure in Definition 3.1 influence the algorithm choice. If sensor and actuator fault share important properties, *i.e.* they can be treated as a unique class of problem (5), plant faults are usually non-trivial to treat, especially when monitoring in real-time scenarios the nominal plant parameters [39].

Since a large part of FDI algorithms is developed for linear systems, it is convenient to introduce the linear case, *i.e.*

$$\iota : \begin{cases} \dot{x} = Ax + Bu + B_w w + R_1 f, \\ y = Cx + R_2 f, \end{cases} \tag{8}$$

where the triple (A, B, C) represent the process, input, and measurement matrix, B_w it the disturbance input matrix, while R_1 and R_2 are the fault input and output matrices.

Remark 4. Eq. (8), accounts for additive faults, nonlinearities (included in the disturbance term w), external disturbances, and uncertainties. Hence, the model in (8) appears complete to treat a fault-tolerant problem in wave energy.

Also the plant properties influence the FDI algorithm choice. For nonlinear systems as is (6), the residual generation/evaluation problem solution is based on elimination theory [41], Gröbner bases [42], or characteristics sets [43]. A nonlinear fault estimator with external input decoupling is in [44], a decoupling scheme based on adaptive nonlinear geometric observers is developed, and can be employed for a large number of nonlinear systems. Nonetheless, in general treating nonlinear FDI problems with unknown inputs is restricted to a reduced set of systems. Consequently, the research has focused on developing robust FDI techniques applied to LTI systems, as described in the following.

Robust FDI algorithms develop residual signals insensitive to external disturbances exploiting a linear model as in (8) to diagnose, if possible, the fault in the system. This subsection gives a brief overview of robust FDI residual generation strategies.

Generally, residual generation techniques can be classified into parity relations, observer-based techniques, and system identification-based approaches.

Parity relations These methods compare, over a time window, direct sensor measurements and indirect relations describing the same quantity obtained with the model in (8) [39]. The space spanned by the residual generation matrix is called parity space. The residual generation structure is given in Fig. 2 where, with reference to system (8) and a generic window of length N, the matrix H is defined as

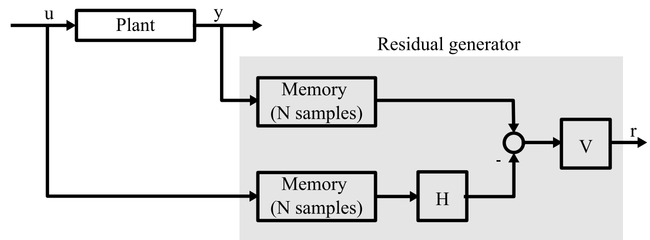

Fig. 2. Residual generation with parity space architecture.

$$H = \begin{bmatrix} 0 & 0 & \dots & 0 \\ CB & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ CA^{N-1}B & CA^{N-2}B & \dots & 0 \end{bmatrix}, \tag{9}$$

and where the matrix V is the design freedom parameter, used to select the sensitivity direction of each residual. A critical aspect regards the robustness of the residuals. A potential solution appeared in [45], which proposed a mixed optimisation problem to make the residual sensitive to faults and insensitive to parameter variations. Nonetheless, the complexity of the multi-objective optimisation problem and the inability to handle noise without actually filtering the residual vector are criticisms.

Observer-based approach FDI observers estimate the desired output based on the measurements in a feedback fashion, and then generate the residuals comparing the estimate and the measure. Such observers can be designed both in a deterministic (Luenberger) or stochastic (Kalman) fashion, according to the problem requirements [39]. The observer structure is the following

$$\iota_o : \begin{cases} \dot{\xi} = F\xi + Ky + Ju, \\ \hat{x} = G\xi + Ry + Su, \end{cases} \tag{10}$$

where matrices (F, K, J, G, R, S) are the associated design parameters. Motivated by their ability to reject undesired inputs, unknown input observers (UIO) gained interest in the FDI field [39]. The advantage behind such structures is the unknown dynamics rejection, such as nonlinearities and exogenous inputs. Achieving robustness is easier than parity relations, since a large part of the uncertainty can be incorporated into the unknown term and rejected at the design stage. The reader can refer to [39] for further details on the design of UIO observers. Even if the observer structure in (10) is the most used, alternative architectures can be employed to achieve fault estimation/disturbance rejection performance. Sliding mode observers (SMO) [46] give a wider flexibility on the uncertain definition, while featuring nonlinearities handling. A different approach consists in defining a performance index between two quantities, *e.g.* the ratio between the fault signal and the unknown input, and solving the observer design via optimisation methods (*e.g.* via $\mathcal{H}_\infty$-design [47]). It has been proved that parity relations and observer-based algorithms are equivalent, under certain conditions [39]. In fact, it is possible to design parity relations and observer-based FDI algorithms also in the frequency domain, a useful strategy if the fault effects have precise spectral characteristics, or if the FDI systems are required to be insensitive to system dynamics in some pre-specified frequency range. Nonetheless, the observer-based approach provides more freedom at the design stage, so these tactics are regarded as more complete architectures.

Remark 5. Observer-based approaches and parity relations are employed to detect actuator and sensor faults. Detecting plant faults with such structures is not trivial. A common alternative to detect faults in system process parameters is to adopt system identification techniques [48].

System identification approach System identification (sysID) FDI aims at estimating, in real-time, the process parameters (or directly the I/O response), detecting eventual variations to the nominal model. If this happens, a fault is detected. A drawback resides in the isolation task, which is complex when the model parameters do not match the system physical variables [39]. Such an issue can be solved with the so-called influence matrix approach [49], which attempts to identify the influence of the residual vector on each physical plant parameter. The robustness depends on the specific algorithm and the possibility of handling eventual nonlinearities/disturbances in the system. Although sysID methods are not the most well-suited strategies for detecting and isolating actuator or sensor faults, it is possible to incorporate actuator/sensor FDI features. Additionally, for identifying the full system dynamics, some sysID exploit properly designed signals to excite the system, which are not always possible to inject in practice.

As highlighted in Fig. 1, the FDI structure entails analysing the residual vector to extrapolate eventual information of the occurring fault. This stage is termed residual evaluation.

Residuals are designed according to the expected output of fault analysis, as detailed in Section 3.1. For detection/identification purposes, the residuals do not necessarily describe the precise fault evolution in time. In this case, the evaluation system must be provided with some criteria to decide rather or not, and eventually where, the fault is happening. The most common technique is to adopt a fixed threshold: if the residual overcomes a predefined value, the fault alarm is triggered, and the component fault is detected [39]. However, a fixed threshold test may result in false alarms, since the proper choice of the threshold itself is not trivial [39]. Statistical tests on the residual are proposed, such as generalised likelihood ratio tests, cumulative sum algorithms, or weighted sum-squared tests, for solving the robustness issue. An alternative approach is to select the threshold adaptively, according to a given functional law. The reader is referred to [39] for further details on such implementations.

3.2. Fault-tolerant control (FTC)

As discussed in Section 1, FTC algorithms accommodate eventual faults to allow the respect of control specification limits. In principle, FTC relied on strategies capable of neglecting/rejecting the fault effects inside the controller-system loop, without real-time knowledge of the actual fault. Such an approach is called passive fault tolerant control (PFTC) [50], and is focused on the controller implementation based on the desired performances under every possible fault scenario. Instead, the idea of using the fault estimate information is called active fault tolerant control (AFTC) [50].

As performed within Section 3.1, and to keep this paper reasonably self-contained, a formal definition of FTC is introduced in the following, adapted from [11].

Definition 3 (*FTC Problem: Behavioural Formulation*)**.** Recalling $\mathcal{B}_0$ and $\mathcal{B}_f$ from Definition 1, and indicating with $\mathcal{B}_C$ the controller behaviour, *i.e.* the I/O pair (U, Y) satisfying the control law, and the closed-loop control specifications behaviour as $\mathcal{B}_{spec}$, the nominal control performance can be defined as

$$\mathcal{B}_0 \cap \mathcal{B}_C \subset \mathcal{B}_{spec}. \tag{11}$$

The fault-tolerant control problem is to design a controller so that

$$\mathcal{B}_f \cap \mathcal{B}_C \subset \mathcal{B}_{spec}. \tag{12}$$

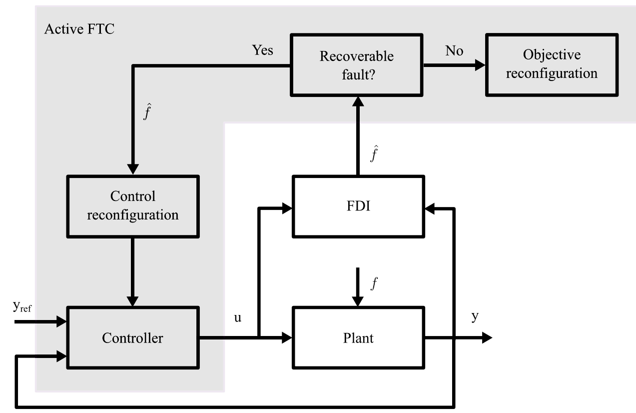

Fig. 3. FTC architecture configuration.

PFTC aims at finding a control law in charge to respect simultaneously both (11) and (12), for every possible fault. Nonetheless, to find a solution without any real-time fault knowledge, the specification set must not be very restrictive, *i.e.* the approach is said to be conservative. Differently, AFTC strategies guarantee better performances, also under severe faulty conditions, due to the use of fault information provided by the FDI system. AFTC architectures have a reconfiguration system, in charge of changing the controller parameters (fault accommodation) or the controller structure (control reconfiguration) [11], according to the information. If passive FTC strategies are implemented as 'standard' control configurations, the structure of active FTC algorithms is given in Fig. 3.

Remark 6. Fig. 3 assumes that the controller redesign block is provided only with the fault information. Supposing the damage in the system is excessively severe, a decision block is in charge of deciding whether or not the control objectives have to be redefined, and eventually provides the new control specifications.

As for the case FDI, discussed within Section 3.1, it is convenient to reformulate the FTC problem in a deterministic fashion.

Definition 4 (*Deterministic FTC Problem*)**.** Find the optimal controller which satisfies the control specifications, using knowledge of the system dynamics in (6) and the fault information f (only for active FTC strategies).

Following what done in Section 3.1, a brief overview of the main FTC algorithms is provided hereafter, following the PFTC/AFTC division.

PFTC strategies PFTCs are reliable controllers without auxiliary FDI algorithms. In PFTC the (possible) set of faulty conditions likely affecting the system dynamics have to be defined. This information is crucial, since, as discussed in Section 2.1 for the robust control case, the controller design is based on the fault modelling. Among PFTCs, $\mathcal{H}_\infty$ optimisation-based techniques [51] exploit the system properties and a-priori knowledge of the faulty dynamics to define worst-case scenarios, over which the control laws are synthesised. Alternative approaches use redundancies to develop control laws ensuring reliability via eigenstructure assignment [52]. Some works recall the idea of $\mathcal{H}_\infty$ optimisation in a multi-objective fashion, simultaneously optimising several I/O channels description under faulty conditions.

Remark 7. PFTC strategies neglect the current fault information, which brings the advantage of analysing robustness/stability properties offline at the cost of introducing some conservatism. Consequently, a higher interest in AFTC has grown, which exploits the FDI fault information.

AFTC strategies AFTCs are designed to enhance the performance of the damaged system/component to PFTC with real-time fault information, while providing reliability for avoiding critical damages. Linear quadratic regulators (LQR) are widely used in AFTC [53]. They use the fault knowledge, to design state-feedback LQR controllers which stabilise the modified dynamics via an automatic routine, such as Youla-Kučera parameterisation -based algorithms [54,55]. They exploit the real-time input–output system description (which eventually is obtained from sysID FDI) for synthesising the new controller. Nonetheless, they carry the same limitations of sysID FDI discussed in Section 3.1. Model following [56] aims, when a fault occurs in the system, at recovering the original (nominal) closed-loop response by modifying the controller parameters. Adaptive FTC strategies [57,58] adopt compensator systems to cancel the fault effect, while retaining the nominal model for initial controller design. Multiple-model approaches [59] exploit a bank of models describing the system in different faulty operation points, which are to be detected to allow the control decision block to select the proper controller. Regarding constraint handling features, FTC has also looked at OC methods, such as MPC, to include the fault dynamics in the system constraint description, hence considering the FDI information directly in the control action optimisation problem [60].

3.3. The role of FDI and FTC in wind energy systems

Considering that FTC and FDI are still immature fields in wave energy, seeking inspiration and example from a mature, affine area, such as wind energy, may constitute a crucial point for their growth and development. In this context, a concise presentation of the FDI and FTC technology in wind energy systems, combined with an analysis of the similarities and differences between the wave and wind applications (from a control-oriented perspective), can provide ideas for a faster and consistent growth of FDI/FTC applied to WEC devices.

Practically, minimising maintenance costs and unproductive periods is crucial also in wind energy, the reason for which FDI and FTC have seen a growing interest in wind turbine research. In this area, the objective is energy maximising, *i.e.* the same pursued by WEC systems, as described in Section 2. Additionally, as in wave energy, wind power systems are affected by an exogenous disturbance (the wind), sharing an equivalent estimation problem described in Remark 2.

Though similar initially, the two control problems present some fundamental differences. In wind, the objective is pursued by tracking a reference rotor speed, which changes accordingly with the given wind condition [61]. In contrast, in wave energy, the objective function in (4) is directly maximised. Also the nature of the external input distinguishes the two problems: wind speed is commonly characterised by recognisable low-frequency components, while wave excitation forces are modelled as wide-spectrum signals, with frequency content changing relatively fast over time. In other words, in wave energy, it is impossible to distinguish between the control action and the wave excitation force based on their amplitude and spectral components.

Remark 8. Both wave and wind energy systems are affected by nonlinearities [62]. Hence, designing the controller based on a nonlinear system approximation is reasonable. Nonlinear control strategies are not trivial to implement, often due to their computational and analytical complexity. In this context, within wind energy, a special class of nonlinear systems, called linear parameter varying (LPV) models [63], are widely studied and used for control purposes. LPVs are based on a set of LTI models, parameterised over a scheduling variable (often the wind velocity). The convex hull generated by the set of linear models composing the LPV system is generally a convex set, thus allowing the exploitation of standard results of linear systems theory [64]. Nonetheless, to the best of the authors' knowledge, LPV models are still not employed within the wave energy field, since a critical aspect resides in the oscillatory behaviour of the wave motion, thus leaving untapped the LPV potential in the field.

In the following, a brief description of relevant FDI/FTC strategies applied in wind turbines is provided, to illustrate their use in a sister renewable field to that of wave energy conversion.

FDI wind energy systems exploit observer-based approaches, parity relations and sysID methods. [65] uses interval observers, characterising the model with parameter uncertainty sets. In [66,67], the authors develop UIOs to detect faults in the drivetrain system, while rejecting the aerodynamic torque disturbance. The residual is tested with generalised likelihood ratio algorithms or fixed thresholds to identify the fault presence. [68] adopts $\mathcal{H}_\infty$ optimisation to design the sensor fault observer and, in parallel, develops an adaptive observer, based on a turbine LPV model, for fault estimation. [69] designs a fault estimator LPV model-based extended state observer. An additional optimisation improves the observer's robustness to exogenous disturbances and modelling uncertainties. In [70], an adaptive step-by-step SMO estimates pressure faults in the pitch control system. [71] focuses the fault estimation analysis on robust Kalman filters, under the assumptions of multiplicative and additive sensor faults.

Speaking of sysID FDI, in [72], a set-membership algorithm estimates and tests the dynamic model with the original (validated) behaviour. This approach exploits a wind speed estimator to reduce the uncertainty set. An advantage is the residual evaluation absence, since the uncertainty intervals are defined at the algorithm design stage. Nonetheless, the computational burden is considerable, and its real-time hardware deployment is questionable. To reduce the computational complexity, a linear autoregressive model is commonly used, as in [73], which is the pseudo-inverse method described in [11]. The computational lightness entails a fixed-structure linear model assumption and allows the coefficient identification of a specific autoregressive model. This strategy can be restrictive in some cases, especially when the equations are excessively approximated under the assumption of a regressor form.

[74] uses the advancements in model falsification theory to build set-valued observers for each system fault. The algorithm evaluates the inconsistency between the observed states and the faultless condition, identifying the fault without requiring residual evaluation. This strategy, like other set-membership algorithms, presents some computational complexity, which still appears to be a prohibitive challenge. Even if observers and sysID are the most common FDI residual generation/fault estimation strategies in wind energy, parity relations are still applied, thanks to their easiness of implementation and effectiveness [75–77].

Remark 9. Given that this study is focused on model-based techniques for FDI and FTC applied to WEC systems, it has been deemed convenient to present the same algorithm categories (as described in Section 3.3) for more mature wind energy field. Nonetheless, it is important to remark that, in wind FDI, a consistent set of studies are based on model-free FDI strategies [78,79].

For what concerns the control part, significant PFTC applications in wind energy are [80,81], where the authors propose a controller synthesis procedure based on LPV model parameter (the wind speed, estimated via robust observer) and fault uncertainty intervals. Within severe degradation conditions, the controller follows the general behaviour of PFTC, experimenting relevant issues.

Remark 10. Wind turbines are controlled such that the rotor axis follows an angular velocity according to the wind speed condition. This logic does not entail a direct power maximisation in the objective function, and can be classified as a trajectory tracking problem. For wind FTC, the authors refer to an additional controller developed not in place of the baseline controller, providing the required control resilience feature characteristic of FTC.

A common AFTC in wind energy is the so-called compensation system, which, relying on the fault estimate, corrects the nominal action with an additional signal for compensating the fault effect on the closed-loop system. [69] develops a compensator for an LPV model by scheduling a bank of controllers according to the wind speed. Such FTC features disturbance rejection properties (achieved via $\mathcal{H}_\infty$ performance index optimisation) and respects the design requirements with a standard pole-placement method. Similarly, [82] exploits the actuator fault estimate to compensate for the total control torque provided to the wind turbine generator. In [65,68,73], FTC is developed using the virtual sensor and actuator principle [11]. This latter consists of designing a proper transfer function to hide the fault presence for the system by manipulating the controller input and sensor output. [83] designs a Ziegler–Nichols-based PI adaptive controller whose parameters depend on the identified system model structure, estimated via a pseudo-inverse method. In [80,81], an active LPV FTC controller is scheduled on the fault and wind speed estimates. Such architecture allows for simultaneous consideration of nonlinearities and the eventual fault presence. Similarly, [68] leverages the fault estimate to reconfigure feedback and a feedforward LPV controller to accommodate the fault effects on the pitch actuator system. [74] proposes a bank of controllers designed for different fault conditions, chosen according to the situation diagnosed by the FDI routine. Speaking of constrained FTC, [84], develops a hierarchical MPC architecture to accommodate faults while respecting the system constraints. The fault tolerance feature is achieved via a cascade interconnection of a supervisory level, a pre-compensator, and a baseline MPC controller, which interact to accommodate the (estimated) fault effects.

4. FDI in wave energy

This section presents the state-of-the-art FDI strategies in wave energy. The wave excitation force estimation problem is, essentially, coincident with the actuator fault diagnosis problem. In fact, in wave energy, the large part of wave estimators actually are FDI techniques, applied to a case which differs only nominally from an actuator fault estimate. Driven by this, and to deliver a complete discussion of fault-tolerance in the field, we include all techniques exploiting FDI algorithms in wave energy, even if their primary scope is that of wave force estimate.

Remark 11. As discussed in Remark 2, a problem is the reliable estimate of the wave excitation force. Some strategies use FDI structures (such as UIO), treating the wave as an exogenous disturbance for the system. The difference between estimation and rejection lives in the performance index. In FDI, the state/fault observer is robust to unmodelled/exogenous dynamics while, in wave force estimation, the external signal is the quantity to be retrieved, *i.e.* maximising its effect on the observed system.

To the best of the authors' knowledge, the first application of FDI for WECs can be found in [85], where the authors propose a fast adaptive actuator fault estimator (FAUIE) to observe the wave excitation force. The adaptive observer uses a nonlinear Lipschitz model, and is obtained with a linear matrix inequality (LMI) optimisation problem via Lyapunov function stabilisation proof. The authors in [86] elaborate the idea to apply FDI architecture for wave estimation by proposing a robust linear UIO to estimate the excitation force. The signal is included in the system state, estimated via UIO, while attenuating the effect of other external disturbances/nonlinearities. The observer parameters are retrieved by $\mathcal{H}_\infty$ optimisation. A similar technique is developed in [87], where the wave excitation force observer is experimented in wave tank facility tests. A subsequent, alternative approach to FDI-based wave estimation is in [88], where an adaptive sliding mode observer (ASMO) estimates the wave force signal. This approach exploits the intrinsic robustness of SMOs, in which the uncertainty intervals are in the differential inclusion describing the observer structure. Additionally, an adaptive law changes the parameters, for improving the estimation effectiveness. Convergence analysis is also provided. Even though the authors do not conceive the ASMO as an FDI technique, the sliding mode FDI application is widely employed, as discussed in detail in Section 3.3. [89] use an adaptive policy for the same observer type, including validation in an experimental tank environment. The same authors of [85,86] propose an additional work exploiting FDI for excitation force estimation purposes in [90]. Here the authors propose an adaptive law which, based on a secondary state observer, retrieves the desired signal. The parameters are obtained via an LMI solution, whose optimality conditions derive from convergence analysis (*i.e.* Lyapunov function constraints). More precisely, the algorithm estimates unmodelled nonlinear effects and the wave force, and consequently, an additional measure (wave elevation velocity) is required for excitation force estimation. Since the observer is designed with a linear system, parametric perturbations can affect its performance.

The earlier application in which a FDI structure is not employed directly for wave estimation can be found in [91], where an adaptive sysID technique is used to estimate the parameters of the linear control-oriented model (an auxiliary Hurwitz polynomials-based description). Even if the authors do not specify the FDI nature of such an approach, it is evident how this strategy scope is consistent with the classification in Section 3.3, *i.e.* identifying model parameters variation to accommodate the controller structure. An adaptive excitation force estimator is used to increase the sysID performance.

Nonetheless, the first studies treating explicitly of FDI in wave energy are [92,93]. Here the authors analyse the structural detectability and isolability of sensor and actuator faults for the Archimedes wave swing converter, a specific type of WEC. From a bipartite graph is retrieved structural conditions for each system fault, *i.e* six residual vectors are derived from the required consistency relations. The necessary conditions of mutual fault exclusion are obtained. Such WEC is controlled via damping injection, *i.e.* a parametric control law proportional with the system velocity. In [93,94], the authors do a further step in wave energy early FDI advancement, by developing a sliding mode UIO to estimate the damping force deviation from nominal conditions. Approximately during the same period of the early work in [92], an atypical, yet effective, FDI strategy is developed in [95], where a graph-theoretic approach is adopted to detect eventual faults. This strategy relies on the availability of multivariate data time-series and Laplacian eigenvectors representing the different failure scenarios. The eigenvectors' spectral analysis allows fault detection and isolation, even with transmission delays and modelling uncertainties.

A critical issue towards a complete and consistent FDI development is analysed by [96], where the authors study the excitation force estimation effects on the FDI module. The observer in [93] is coupled with a Kalman filter which estimates upper brake failures, and analyse the FDI results changing the wave excitation force estimator. Simultaneously with [96,97] propose a linear UIO (see Section 3.3) applied to WECs, in which the observer decouples the fault estimate from the wave excitation force. The design parameters are derived from a LMI solution, whose problem constraints regard stability analysis. [98] proposes a similar fault observer-based estimator detecting sensor damages (position/velocity) with a linear observer. At the same time, an auxiliary adaptive law (based on the observed output error) detects the actuator fault. The observer exploits the control action and the excitation force estimate, while the adaptive law convergence (and hence the estimator parameters) is demonstrated via Lyapunov analysis. The recent work of [99] instead, overviews the FDI problem in wave energy, and proposes a stratified architecture (even though not describing any particular algorithm) based on high-fidelity models for checking the behaviour consistency of the actual system.

4.1. FDI possibilities in wave energy

This section analyses the advantages of wave energy FDI. Such discussion highlights the incentives for moving towards the effective development of FDI in this field.

As discussed in Section 1, FDI in a power production system allows one to execute maintenance operations more efficiently, saving considerable economic resources. Additionally, FDI algorithms retrieve a considerable amount of redundant information about the components' state, making additional hardware monitoring components superfluous. Such information helps avoid severe WEC damages, by driving device breaking-down decisions in case of critical fault detection. Nonetheless, the primary value of FDI application is the synergy with AFTC architectures. AFTC systems are more effective than their passive counterparts, at the cost of requiring faults' information.

FDI structures (especially UIO observers as in [97]) efficiently estimate the system states/outputs independently from the excitation force knowledge. As discussed in Section 3.3, in wave energy, it is not trivial to separate the control action and the wave contributions when no force estimators are employed. In this context, UIOs help reject unmodelled dynamics/disturbances (*e.g.* the wave force) while estimating the system states.

Similarly, it is possible to detect/isolate/estimate fault effects while separating the excitation force and other unmodelled dynamics. FDI algorithms entail robustness properties to model parameter uncertainties [88,93], which enables estimate reliability without requiring exact models. This concept is fundamental, since the approximation of hydrodynamic forces introduces a significant source of uncertainty, as discussed in Section 1.

In (8), the input dynamics (input matrix) of the actuator is coincident with that of the excitation force [97], allowing to treat the wave force analysis as an FDI actuator estimate. Such property is of paramount importance, allowing the employment of well-established FDI techniques for reliable wave estimation (see Remark 11).

With the opposite perspective, it is possible to use wave estimation algorithms to detect and isolate faults in the WEC actuator system. This reflection gains further interest following the consideration in [11], where actuator and sensor FDI problems are demonstrated to be equivalent (under given conditions). UIOs brig the advantage of decoupling nonlinear/unmodelled effects from the wave contribution, since both are treated as unknown inputs. Another point favouring FDI is their ease of implementation, since they usually do not rely on real-time optimisation (except in some sysID-based strategies).

4.2. FDI pitfalls in wave energy

In wave energy FDI, the first issue coming to the eye is the counterpart of Remark 11 consideration: the superposition of the actuator and wave force input dynamics. While this can be useful to leverage FDI techniques for excitation force estimation, it represents a problem regarding FDI in operating conditions. The observer's structural insensibility to the wave force coincides with the practical rejection of actuator faults, making it impossible to detect eventual actuation failures.

To circumvent such an issue, some studies [93,98] directly measure (which is not a reasonable assumption in practice) or estimate [91, 94,96] the wave excitation force, to recover the observer sensibility to actuator performance breakdown, though implying some robustness degradation. In [94], the authors claim to solve the problem with a direct multi-step excitation force estimator, which is not designed based on a WEC model. Nonetheless, the provided force estimate is not, in general, accurate [20], thus frustrating the advantage of neglecting the model. Following the discussion in Section 4.1, error sources are always present in WEC control-oriented models, thus compromising both the state/output and fault estimation (if not adequately accommodated) [85,90]. Though the wave excitation force in FDI brings precision advantages [91,96], the analysed structures employ a nominal system model. In faulty cases, such deviates from the current system dynamics; consequently, some robustness in wave estimation is lost.

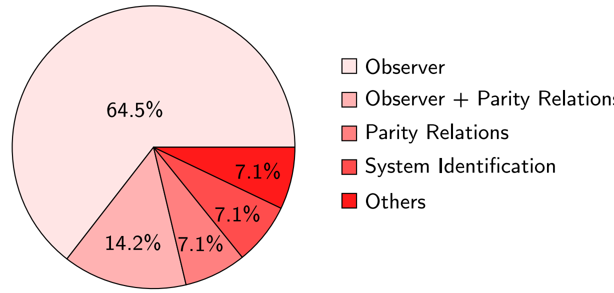

Fig. 4. FDI in wave energy: strategy type.

In wave energy FDI, the authors consider additional studies on FDI system/wave estimator coupling to be a fundamental step. Wave estimators based on UIOs retrieve the total contribution of the unmodelled effects and the wave force [85,87], necessitating additional measures for effect separation. [86] tackles this issue using the wave elevation information, at the cost of installing wave probes/inertial motion units on the device. A recurrent approach is to estimate the fault vector using a UIO for an augmented system, whose states are the union of the WEC model states and the fault vector [86,87,97,98]. The structural drawbacks regard the necessity to model the fault with specific dynamic behaviour. For instance, [86,87,98] model the fault as a random walk signal (*i.e.* $\dot{f} = \epsilon$, where $\epsilon \in \mathbb{R}$ is a random number with a given distribution), while [97] employees a ramp model (*i.e.* $\ddot{f} = 0$). Though consistent with the framework the authors consider, such assumptions do not span a sufficiently large fault case set in a general WEC scenario. In other words, if the failure dynamics vary significantly from the model, a misleading result is obtained. Moreover, the UIO structure requires specific rank conditions between the fault input matrix (*i.e.* R_1 and R_2 in Eq. (8)) and the available measurements (*i.e.* C in Eq. (8)), which are not always respected. Despite entailing additional costs, such conditions are recovered by installing extra sensors on the device.

For sysID FDI algorithms, a plausible problem is the impossibility of spanning with properly designed excitation signals the device characteristic frequency range. Therefore, the associated computational burden constitute a barrier to developing real-time sysID FDI. To provide a comprehensive view of this section, Table 2 presents the main features of the analysed studies in compact form.

Fig. 4 shows how much of the work is focused on observer development, while a lower segment of FDI techniques is based on the remaining principles.

In parallel, Fig. 5 underlines the ability of all the analysed FDI techniques of detecting and isolating the presence of faults, while the estimation feature still remains common. Regarding the analysed damages, the actuator fault is the most studied category, followed at long distance by the sensor and the parameter type.

5. FTC in wave energy

The FTC algorithms applied within the WEC literature are presented in the following section, including an account of their functional aspects. Additionally, to provide a complete comparison and useful feedback for wave energy FTC development, a selected subset of studies related to data-driven [100], robust [36,86], and adaptive control [91], are also presented within this section. These studies present significantly affine features with the state-of-the-art FTC strategies, and hence constitute fundamental steps towards a full understanding (and advancement) of wave energy FTC research.

Though not a model-based strategy, the first work accommodating a faulty condition in a wave energy application is [100]. The authors employ an adaptive, model-free control approach. An artificial

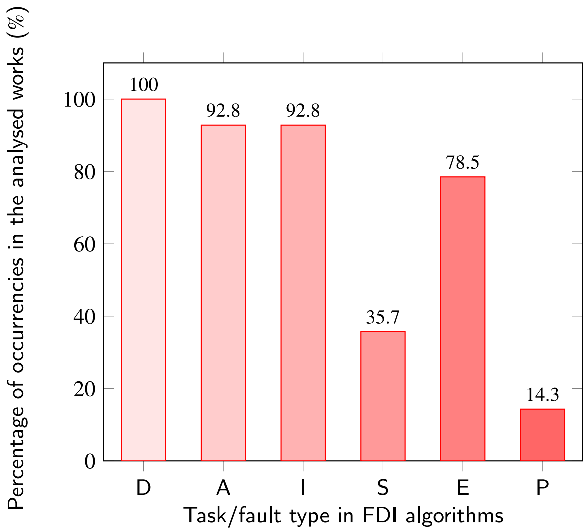

Fig. 5. Percentage of task and type of recognised fault of the algorithms in Table 2. The reader is referred to Table 1 for chart names interpretation.

neural network architecture sets the reference point of the rotor/grid side converters, the valve flow rate, and the crowbar attitude of an oscillating water column. Internal tracking controllers follow the generated references, according to the air chamber pressure drop and the grid voltage measures. Further studies in data-driven FTC for wave energy conversion are [101,102], where a model-free reinforcement learning-based FTC accommodates both actuator and sensor failures.

Differently, [103], which constitutes the first study of FTC applied to wave energy, analyses PFTC applicability for WECs and presents sufficient conditions for developing stable PFTC control laws. Such a condition, which is based on input-to-state stability [104] for a Takagi–Sugeno (TS) nonlinear model, considers the faults as norm-bounded structured uncertainties, and deals with them in the LMI solution associated with the PFTC law. The only other work of wave energy PFTC is in [94], where a variable structure control law, which does not require either excitation force information, acts as a nonlinear compensator to minimise the tracking error between the system trajectory and the reference optimal profile.

For what concerns the robust control strategies, which in some sense present similarities with PFTC approaches, [86] develops a sliding-mode controller to track the optimal position profile generated by an IM controller, under model uncertainty. Similarly, the successive work [36], develops a robust moment-based energy-maximising strategy, capable of respecting input and state constraints with a significant model-system discrepancy in the hydrodynamics of the viscous drag force. For both [36,86], a wave excitation force estimator is required.

An affine application with AFTC is in [91], where the authors develop an adaptive MPC exploiting a linear WEC model changing according to the sysID results, when a parametric discrepancy between the simulation model and the control design model is introduced. The authors consider only uncertainty in the hydrodynamic forces and exploit online sysID to reconfigure the MPC optimisation problem (and the auxiliary state observer). A reliable estimate of wave force is also used for reaching the (approximated) optimal condition. The similarities with system identification-based AFTC algorithms are evident, thus allowing to include [91] within the AFTC set.

The work of [103] is followed by [105], where the authors propose an application for WEC FTC regarding a permanent magnet linear generator used for direct drive energy extraction under reduction of electromagnetic thrust. Similarly, [106], designs a structure of two MPCs to recover from open switch fault on the voltage source (both from the device and grid side), but does not entail, analogously with [106], a power maximisation criterion of the mechanical and hydrodynamics part of the WEC system. From this perspective, the earlier complete work is in [93]. Relying on the damping factor fault estimate (*e.g.* a friction increase), an AFTC compensator shifts the WEC trajectory towards the optimal condition. The strategy is also effective with concurrent faults. [97], similarly with [93], designs a compensator system which modifies the nominal control law to recover the optimality condition, based on a UIO fault estimate. The such compensator manages to accommodate faults of different nature (*e.g.* offsets, linear drifts, sinusoidal additive noises) on the available sensors and actuators, while respecting energy-maximising conditions.

For what concerns recent works, [107] develops an adaptive, multi-controller-based FTC to track the reference trajectory (generated with any OC), while accommodating the system faults, which comprise both actuator lock-in-place and loss of effectiveness conditions. Both the tasks are fulfilled via P learning-based adaptive laws, designed to ensure given $\mathcal{H}_\infty$ performances and Lyapunov stability conditions. The compensation principle is also employed in [98], where the $\mathcal{H}_\infty$ performance index, together with Lyapunov convergence analysis, leads to an LMI problem to obtain the multi-body system actuators nominal controllers. Based on the adaptive estimator information, the compensator keeps the system on the baseline feedback energy-maximising controller trajectory under linear and sinusoidal sensors and actuator faults, representing respectively parasite signals and corrosion processes.

5.1. FTC possibilities in wave energy

This section focuses on the advantages of FTC in wave energy. Such analysis comprises the motivations behind developing FTC techniques on WEC devices.

As discussed in Section 1, the commercialisation of WECs is yet hindered by economic feasibility reasons, among which is maintenance costs. By leveraging two aspects, FTC systems can reduce this expenditure and increase reliability. The first is accommodating potential malfunctions, thus limiting shutdown periods. The second regards avoiding severe damage to faulty components, reducing the repairing intervention cost since soft damages are cheaper and faster to be fixed. Such properties also lower the urgency of maintenance interventions, thus allowing an efficient schedule of operations.

It is well-known that systems affected by stochastic disturbances (such as wind turbines and WECs) present significant challenges towards developing data-based predictive maintenance systems [108,109]. Thus FTC is seen as a potential alternative for avoiding severe damages. Another benefit of FTC in wave energy is their robustness to model uncertainties, which, as discussed in Section 1, are critical in wave energy control. This concept is exploited in [94], where the variable structure control law entails resilience towards modelling errors, while tracking the optimal trajectory. Using two control strategies (the reference generator and the tracking loop) appears to have potential for robustness/fault resilience, since it allows adopting robust strategies that do not necessarily implement energy-maximising criteria.

Eventually, parameter uncertainties can be treated as faults, and thus handled FTC for reliable power production results. Most OC strategies for WECs exploit linear models. Nonetheless, WECs' nonlinear dynamics can mine the efficiency of LTI-based OC algorithms. In this context, FTC can treat the nonlinearities as full-fledged faults, *i.e.* to provide a control action compensating such effects and restoring the optimality.

5.2. FTC pitfalls in wave energy

Even though FCT can bring major advantages in wave energy, structural limitations must be carefully considered.

The first issue regards the solution optimality under faulty conditions. OC algorithms are developed for faultless systems, hence optimality is not guaranteed when the system is affected by fault. In wave energy literature, there still needs to be a vast development regarding

Table 1
Abbreviations and Notations/Symbols legend.

Abbreviations	Full name		
DoF	Degree-of-Freedom	OBUIE	Observer-based unknown input estimator
OC	Optimal control	EM	Energy-maximising
WEC	Wave energy converter	RT	Reference tracking
FDI	Fault diagnosis and identification	GO	Grid operations
FTC	Fault tolerant control	OBS	Observer
DoF	Degree-of-freedom	ANN	Artificial neural network
LTI	Linear time-invariant	ISS	Input-to-state stability
NL	Nonlinear	SMC	Sliding mode control
LPV	Linear parameter varying	MPC	Model predictive control
TS	Takagi–Sugeno	IM	Impedance-matching
MF	Model-free	MO	Moment-based control
I/O	Input–output	COM	Compensator
sysID	System identification	NLCOM	Nonlinear compensator
PFTC	Passive fault tolerant control	BAC	Bayesian critic control
AFTC	Active fault tolerant control	ILBAC	Iterative learning-based adaptive control
RC	Robust control	**Notations/Symbols**	**Full name**
LQR	Linear quadratic regulator	$\mathbb{R}$	Rational number set
PI	Proportional integrative	$\times$	Set cartesian product
LMI	Linear matrix inequality	f	System fault
D	Detection	$\mathcal{F}$	Possible fault set
I	Isolation	$\mathcal{U}$	Plant input set
E	Estimation	$\mathcal{Y}$	Plant output set
A	Actuator	$\mathcal{B}$	System behaviour
S	Sensor	U	Input sequence
P	Parameters	Y	Output sequence
RW	Random walk	$\{\hat{\cdot}\}$	Signal estimate
LF	Linear fault	$\{\dot{\cdot}\}$	Signal time derivative
WE	Wave estimation	J	Cost function
ESS	Estimated excitation force	T	Time horizon
EXK	Exact knowledge excitation force	t	Time
PU	Parameter uncertainty	$z, \dot{z}$	WEC displacement and velocity
NLs	Nonlinearities	u	Control action
AE	Adaptive parameter estimator	x	System state vector
FAUIE	Fast adaptive unknown input observer	w	Wave excitation force
UIO	Unknown input observer	g	State mapping
ASMO	Adaptive sliding mode observer	h	Output mapping
SMUIO	Sliding mode unknown input observer	i_m	Motor current
CR	Consistency relations	Δp	Pressure drop
MTS	Multivariate time series	V_g	Grid voltage

Table 2
Comparison between the main characteristic of the reviewed FDI strategies.

Reference	Model	Task			Fault			Fault	Wave	Modelling	Strategy				Structural	Measures
		D	I	E	A	S	P	modelling	information	errors rejection	SysID	Observers	Parity relations	Others	analysis	
[85]	NL	•	•	•	•				WE			AO				x
[86]	LTI	•	•	•	•	•		RW	WE	PU + NL		UIO				$z, \dot{z}$
[87]	LTI	•	•	•	•			RW	WE			UIO				$z, \dot{z}$
[91]	LTI	•					•		ESS	PU	AE					$z, \dot{z}$
[88]	LTI	•	•	•	•				WE	PU + NL		ASMO				$z, \dot{z}$
[89]	LTI	•	•	•	•				WE	PU + NL		ASMO				$z, \dot{z}$
[90]	NL	•	•	•	•				WE	NL		OBUIE				$z, \dot{z}$
[92]	NL	•	•		•	•			EXK				CR		•	$z, \dot{z}, w, i_m$
[95]	MF	•	•		•	•	•		EXK					MTS		$z, \dot{z}, w, i_m$
[93]	NL	•	•	•	•	•			EXK			SMUIO	CR		•	$z, \dot{z}, w, i_m$
[94]	NL	•	•	•	•				ESS			SMUIO				$z, \dot{z}$
[96]	NL	•	•	•	•				ESS			SMUIO	CR			$z, \dot{z}, \eta_\omega$
[97]	LTI	•	•	•	•	•		LF		NL		UIO				$z, \dot{z}$
[98]	LTI	•	•	•	•			RW	EXK			AO				$z, \dot{z}, w$

solution quality for the optimum, especially in the case of OC strategies. In the authors' view, such an aspect must be investigated to guarantee systematically acceptable operation.

In PFTC, conservatism is the most critical issue. Given PFTCs are a subclass of robust control, the reasoning in Remark 7 also holds for them. A large set of faulty conditions/model uncertainties negatively influences energy production in faultless conditions. Shutdown time operation avoidance can hardly compensate for the nominal scenario performance comprising a large part of operational time. In a hierarchical control structure as in [94], the controller is appointed to generate energy-maximising trajectories, while a feedback inner loop (most likely the PFTC strategy) tracks the trajectory while accommodating faults. The optimality guarantee remains an open issue, *i.e.* the energy-maximising control law does not necessarily provide an optimal solution under faults. According to the authors, this motivates the development of FTC techniques with autonomous energy-maximising criteria.

As discussed in Section 2, WEC OC must respect motion and actuator constraints. This principle also holds for FTC systems, which must provide resilience to faults while respecting system limitations. Obtaining a balanced OC/FTC action which respects the imposed constraints is not trivial. For sysID-based FTC, mathematical models describing the system over a (reasonably) complete frequency range are fundamental.

Table 3
Feature comparison of the FTC analysed strategies.

Reference	Model	Task	Fault			Type	Auxiliary FDI	Algorithm	Wave information	Modelling errors rejection	Hard constraints	Measurements
			A	S	P							
[100]	MF	GO						ANN				Δp, V_g
[103]	NL	EM			•	PFTC		ISS				x
[86]	NL	RT			•	RC	OBS	SMC	ESS	NL + PU		z, $\dot{z}$
[91]	LTI	EM			•		SYSID	MPC	ESS	PU	z, u	z, $\dot{z}$
[36]	LTI	EM			•	RC		MO	EXK	PU	z, u	z, $\dot{z}$
[93]	NL	EM	•	•		AFTC	SMUIO	COM	EXK			z, $\dot{z}$, w, i_m
[94]	NL	RT	•			PFTC		NLCOM		NL+PU		z, $\dot{z}$
[98]	LTI	RT	•	•		AFTC	AO	ISS	EXK			z, $\dot{z}$, w
[101]	MF	EM	•					BAC	EXK			z, $\dot{z}$, w
[102]	MF	EM	•	•				BAC	EXK			z, $\dot{z}$, w
[97]	LTI	EM	•	•		AFTC	UIO	COM	ESS	PU + NL	z, $\dot{z}$	
[107]	LTI	RT	•			AFTC		ILBAC	EXK			x, z, $\dot{z}$

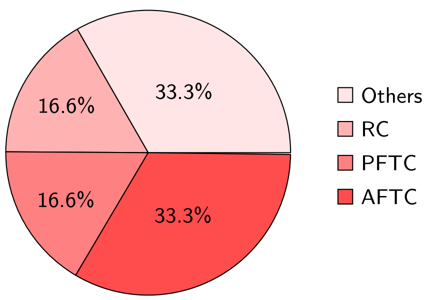

Fig. 6. FTC in wave energy: category type percentage of the analysed works in Table 3.
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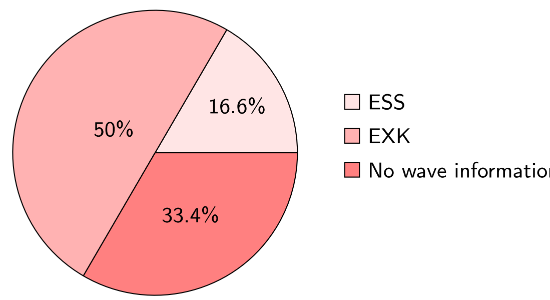

Fig. 7. FTC in wave energy: usage of the wave information if the strategies in Table 3.

In a given time window, the wave exciting force can be characterised by a specific, narrow-banded spectrum, which varies approximately every 30 [min] [110]. Consequently, the wave excitation force input is not sufficient to fully characterise the model (This is, in essence, linked to a fundamental property in system dynamics referred to persistence of excitation see e.g. [111]). Although the PTO system can provide sufficiently exciting signals to retrieve a complete system response for prototypes or small-scale devices, the development on large-scale systems is still pending to be solved. Especially, PTOs capable of providing the required signals on large-scale systems are still unavailable, and the distinction between PTO input and the wave excitation force is still challenging.

To the best of the authors' knowledge, state-of-the-art wave energy AFTC algorithms do not entail per se any power maximisation criterion when handling faulty scenarios. Commonly they track, with a fault-tolerant approach, optimal trajectories generated by external controllers, [97,107]. This characteristic has no general guarantee that the faulty system retains the original optimality condition as the nominal (faultless) system. [91] proposes a solution by optimising the control action based on the identified faulty dynamics, despite retaining the limits of system identification on large-scale wave energy systems. Most of the strategies of Section 2.1, especially OC algorithms, use the wave force knowledge for control optimisation. Such signal is usually estimated (see Remark 2) with model-based observers, which provide reliable solutions with accurate models, and with a fault, the system-model mismatch can lead to a deceptive estimation. Consequently, the authors deem to be necessary to develop wave estimation strategies dealing with model uncertainties and faults.

A comparison of FTC wave energy literature in Table 3 provides a critical overview of the techniques reviewed in this section.

In Fig. 6, the concept discussed in the section, for which in wave energy a more suitable choice is the development of AFTC algorithms, is proven since a large part of the analysed strategies belongs to this category. Nevertheless, PFTC, robust control and other techniques are still finding their spot, distributed equally among the considered works.

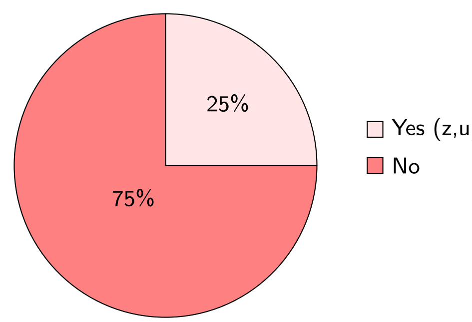

Fig. 8. Percentage of constraint handling capability of the algorithms in Table 2.

The works show an almost equal distribution of the wave information role for FTC, with a light predominance of the signal estimate/knowledge employment, as shown in Fig. 7. This shows that the excitation force role for wave FTC is in discussion, and that there is still no clear evidence on the path to follow.

The constraint handling feature is still to be systematically included in wave energy FTC, as evidenced in Fig. 8, showing the overall percentage of the strategy, including a hard constraint handling routine.

6. Discussion and future directions

This section proposes a concise discussion of the analysis provided in Sections 4 and 5. Nonetheless, since the field is developing rapidly, the proposed critical elaboration (*e.g.* the future directions proposal) is limited by the current state-of-the-art scenario, which can potentially change in a relatively short time. The wave energy control problem belongs to the family of optimal control theory, though with a significant difference in the objective function definition from standard application, which aims at maximising the energy extraction rather than tracking a given trajectory. The harmful WEC operational environment can lead to system malfunctions, compromising the efficiency of OC and the overall system reliability. In addition, OC in faulty conditions may worsen the damage of the system, if not informed of the WEC components' status.

In the light of such considerations, WEC systems shall be provided with control architectures able to deal with faulty scenarios, compensating for any fault effects on the associated mechanical systems. In this context, FDI and FTC algorithms can bring significant advantages to the wave energy field, avoiding the inherent need for shutdown periods and the risk of worsening the system's conditions.

Despite the attractive features of FDI/FTC solutions, these also bring some issues, which are only partially covered by the currently limited literature within the wave energy field. The first problem, as discussed in Section 5, is the control solution optimality under faults. When a fault is present, the OC provides an energy-maximising solution without considering the device degradation, *i.e.* the mismatch of the faultless dynamics and the actual system behaviour. In this context, the FDI/FTC algorithms act by accommodating, via compensation or control reconfiguration, the fault effect at the OC eyes, as in [97], but does not entail per se any guarantee of the control action optimality. Recalling that, as discussed in Section 2, the final control objective in wave energy is that of energy maximisation, the control optimality question under FTC conditions is to be carefully addressed in order to fully exploit the discussed technology. A possible solution is developing FTC strategies which directly maximise energy extraction, while providing fault-tolerant features, *i.e.* it is necessary to solve problem (4) while incorporating the fault dynamics in (8) (for the linear case): so that, fault accommodation optimal power extraction capabilities are provided simultaneously, hence solving the (apparent) conflicting problems. Nonetheless, a challenge of this approach is constituted by the nature of the faults. The actuator/sensor and plant fault problems are addressed via different strategies, meaning that a cautious fault estimate signal routing, in case of concurrent fault, has to be considered. Additionally, up until today, the plant fault scenario, which in the authors' vision constitutes the most relevant (and non-trivial) fault to be accommodated under energy maximisation conditions, is still not investigated in the wave energy field. This uncertainty poses some relevant questions, such as the optimal control problem regularisation under faults. The cost function in (4) differs significantly from the standard tracking objective. For tracking purposes, in direct OC formulations, one can virtually always guarantee transcription to a convex optimisation problem, which can be usually solved leveraging real-time convex optimisation algorithms. On the contrary, Eq. (4), is associated with a non-convex quadratic programming problem [22]. A standard solution resides in modifying the cost function in (4) with an additional term [112], regularising the problem and obtaining the relative (approximated) solution via convex solvers. The discussed regularisation depends on the plant structure and parameters (*i.e.* the control-oriented model). Consequently, such regularisation routine is to be included in energy maximising FTC structures, especially the in algorithms entailing system identification procedures.

Regarding PFTC in wave energy, a major drawback, as discussed in Section 5.2, is the conservatism introduced with a large uncertainty set, since a direct consequence is the consistent loss of energy production capacity, even though with an exception related to the work of [94]. AFTC appears to fit better in wave energy context than PFTC since the direct exploitation of fault knowledge allows the development of strategies with better performance, which in this particular application is traduced in lowering the wave energy cost. Another aspect is the necessity to constrain the controlled motion of WEC devices (see Section 2). A large part of the analysed works does not entail any hard constraint routine in the WEC motion, which is, practically speaking, a mandatory feature for a WEC control algorithm. An exception is in [91], where the inherent MPC capability of solving the optimisation problem, including hard constraints for control and state variables, is used. In the authors' view, the capacity of different WEC FTC strategies must be investigated, given that the fault-tolerance feature is full-fledged useless without the possibility of handling the physical limits of the system, especially in an environment where external factors heavily influence the controlled system motion.

As highlighted in Section 5.2, the wave excitation force is characterised by a spectrum that changes over time and generally does not completely span the relevant frequency range of a WEC. Consequently, the I/O pairs collected in a limited time, do not sufficiently describe the entire spectral behaviour of the device. Hence, standard system identification-based FTC/FDI algorithms are likely to describe only partially the desired nominal (and faulty) dynamics, over which the control strategy is tuned. This limitation has to be carefully considered, because an incorrect control synthesis can lead to dangerous misbehaviours. Two different solutions seem to be reasonable. The first is applying a properly designed input with the PTO system, so that the WEC I/O measured response characterises sufficiently well the operational frequency range. However, a limitation is encountered when decoupling the effects of the wave excitation force from the identification signal. Additionally, the PTO system must be chosen according to the system identification algorithm requirements, which are not a priori coincident with the optimal control requests.

An alternative is to build offline a set of faulty models, and check the consistency of the actual system I/O response in real-time. If the test produces a positive outcome, the system is employed for the control synthesis. Here the major challenge is producing a sufficient number of systems which properly characterises the set of possible faults, and must be reasonably exhaustive while not producing any I/O overlap when the system is operating in real conditions.

An open point in wave energy FDI is handling the wave excitation force. The FDI field is full of algorithms intended to estimate the fault effects while rejecting immeasurable (or undesired) dynamics, which is promising to decouple the wave excitation force from a possible fault estimate. Nonetheless, when speaking of actuator faults, the control and the wave excitation force input coincides (*i.e.*, regarding Eq. (8), the matrices B and B_w are the same). Consequently, if the observer is insensitive to w, it cannot detect variations in the actuator behaviour with such a dynamic model. However, in [93] the authors exploit the wave excitation force knowledge to estimate eventual actuator failures. In contrast, [97] develop a UIO insensitive to the excitation dynamics and sensitive to the analysed actuation faults. This is achieved by assigning a dynamical model to the fault, and detecting eventual deviation from the expected behaviour. Nonetheless, as remarked in Section 5.2, such an assumption is valid only for a limited set of faults, and cannot be applied for general, fault model-agnostic detection purposes. A different consideration is done while detecting sensor faults, since the measurement dynamics differ from the wave excitation force, thus allowing sensor FDI while rejecting the wave excitation signal.

From the previous discussion, it arises how it is deemed useful to retrieve the wave excitation force not only for OC (as highlighted in Remark 2), but also for FDI and FTC. Nonetheless, the most common (and effective) wave excitation force estimators rely on the nominal system model, which does not guarantee a proper description of the system dynamics in case of a fault. Some FDI/FTC routines, which estimate the fault in real-time, rely on wave estimators, which depend on the fault itself, generating a vicious circle compromising both the wave and fault estimate. In the authors' view, in case of impossibility to neglect the excitation force in FDI/FTC, it is necessary to include the ability to deal with faulty dynamics within the wave estimation routine, adding fault tolerance features also to these fundamental subsystems.

Speaking of the untapped possibilities of FDI and FTC in wave energy, the effective development of LPV models for WECs can lead to significant improvements on both the robustness and effectiveness control side (a result which can be directly extended to OC). Nonetheless, as discussed in Remark 8, such a task appears to be challenging, mainly due to the oscillatory behaviour of the input wave excitation force. An additional aspect regards the absence of wave energy studies in residual threshold evaluation, which in case of isolation tasks (see [92]) are fundamental to introduce robustness properties for the FDI system.

6.1. Conclusions

In summary, it can be concluded that the current status of FDI and FTC within wave energy conversion is not developed as other fields, like wind energy, and still needs major steps to set its tone in the WEC control field. Even if such strategies can bring significant advantages to WEC safe operations, FDI algorithms must be developed to cope consistently with the uncertainty introduced by the wave motion, especially with the detection limitations related to the eventual rejection (or usage) of such excitation force signal. For system identification FDI, it is of paramount importance to carefully consider the description which can be obtained for the system model, in the small-medium time range, given the wave force current spectrum. On the control side, the direct inclusion of the energy maximisation principle in the FTC development appears to be a fundamental point of discussion, since the optimality of the control solution depends also on eventual faults. In parallel, it is fundamental to investigate more deeply how to implement real-time feasible FTC structure, which can maximise power production while respecting imposed constraints on the system's physical variables. Solving such problems is fundamental to unlocking the development of reliable and effective FTC/FDI, a possible answer to opening economic possibilities in wave energy.

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

No data was used for the research described in the article.

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