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Review

Health-sensitive control of wave energy converters: A primer

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ABSTRACT

In pursuing environmental sustainability and reducing carbon footprints, wave energy converters (WECs) will play an important role in harnessing the immense energy embedded in ocean waves. While WECs have promising potential to meet global energy needs, their technology performance level is lower than that of solar and wind devices, leading to a higher levelised cost of energy (LCoE). Over the last two decades, researchers have primarily focused on developing control technology to create more effective controllers, designed to manipulate the motion of WECs aggressively, aiming to maximise their energy-harvesting capacity in an effort to minimise the LCoE. However, exaggerated WEC motion can, in the harsh ocean environment, lead to significant decreases in maintenance intervals and system reliability, leading to increases in operational costs (OpEx). There may also be an adverse effect on device lifetime, as well as the inevitable LCoE increases associated with increased OpEx. This paper aims to define the lifespan control problem for WECs by reviewing current advancements in longevity analysis within the wave energy application area, as well as other pertinent areas. The obstacles and opportunities for future research will also be covered.

Contents

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Nomenclature

Abbreviation

CapEx	Capital costs
CS	Control sensitive
LCoE	Levelised cost of Energy
MOO	Multi-objective optimisation
MPC	Model predictive control
O&M	Operation and maintenance
OpEx	Operational costs
PTO	Power take-off
PV	Present value
WEC	Wave energy converter

Symbols

η	Wave elevation
E_c	Captured Energy
f_d	Diffraction force (N)
f_v	Viscous drag force (N)
f_{ex}	Wave excitation force (N)
f_{FK}^{dyn}	Dynamic Froude–Krylov force (N)
f_{FK}^{st}	Static Froude–Krylov force (N)
f_{PTO}	Power take-off force (N)
m	Mass of the buoy (kg)
m_∞	Additional mass at infinite frequency (kg)
R_d	Discount rate
s_h	Restoring coefficient matrix
t	Time (s)
u	Control signal
x	State vector of the WEC model
x_r	State vector of the radiation subsystem
y	System output
Y_r	Project lifetime (in years)
$z, \dot{z}, \ddot{z}$	Heave displacement (m), velocity (m/s) and acceleration (m/s^2)

1. Introduction

Environmental issues like global warming and deterioration in air and water quality have so long motivated researchers, industries and policymakers to replace finite natural resources such as fossil fuels with abundant, clean energy resources, such as wind, solar and ocean waves. Compared to solar and wind energy, wave energy is relatively consistent and predictable (Fusco et al., 2010), has higher energy density, and is a relatively underexploited renewable energy source (Bhattacharya et al., 2021; Reikard et al., 2015). Therefore, wave energy has a great potential to satisfy global energy demand in the near future. However, wave energy has, to date, achieved relatively little penetration, due to the lack of commercial competitiveness (Guo and Ringwood, 2021b).

For evaluating the commercial potential of wave energy technology, technology performance level (TPL) is a crucial metric (Weber et al., 2013). In the literature, increasing TPL is usually interpreted as reducing the levelised cost of energy (LCoE), which gives a good assessment of the cost of converting the kinetic and potential energy of waves to electricity. Although the LCoE of wave energy is currently more expensive than other renewable energy resources, such as wind energy (Astariz and Iglesias, 2015), LCoE alone cannot articulate the value of wave energy (i.e. complementarity with other renewables, demand matching, etc.) (Said et al., 2023a; Görmüş et al., 2024).

As mentioned above, the primary fundamental performance metric for WECs is LCoE. LCoE is usually defined over a project lifetime (in years) as (Ringwood et al., 2023):

$$\begin{cases} \mathrm{LCoE} = \frac{\mathrm{PV(CapEx)}+\mathrm{PV(OpEx)}}{\mathrm{PV}(E_c)}, \\ \mathrm{PV(Q)} = \sum_{y_r=y_r^0}^{Y_r} \frac{\mathrm{Q}(y_r)}{(1+R_d/100)^{y_r}}, \end{cases} \tag{1}$$

where R_d is the discount rate, Y_r is the project lifetime (in years), and PV is the present value of a quantity, such as Q. The three primary LCoE parameters, E_c, CapEx, and OpEx, are defined as follows:

- **CapEx (capital costs)**: Typically, CapEx covers the cost of one converter and installation, as well as the cost of electrical cabling, moorings, substation, and electrical installation (Astariz and Iglesias, 2015).
- **OpEx (operational costs)**: Generally speaking, OpEx consists of charges for operation and maintenance (O&M), insurance, ongoing business, administrative, and legal services (Clark et al., 2019).
- **E_c (captured energy)**: E_c is defined as the integral of the transformed power:

$$E_c = \int_0^T x_2(t)u(t)dt, \quad t \in [0, T] \tag{2}$$

where $u(t)$ is the control force and $x_2(t)$ is the velocity of the device (see Section 2 for more detail).

It is worth noting that CapEx can be directly calculated based on physical parameters in the WEC design stage, such as the type of material needed for the hull structure, PTO maximum force and stroke, etc. Teillant et al. (2012). However, considering the dearth of available operational data, in the literature OpEx is typically estimated as a proportion of CapEx (deCastro et al., 2024).

Recently, control systems researchers have considered absorbed energy as a surrogate measure of LCoE, and researchers have designed aggressive controllers to maximise captured energy (Ringwood et al., 2023). To do real-time control, researchers mostly have transformed the LCoE minimisation problem to maximising captured energy (Pasta et al., 2023; Faedo et al., 2017; Ringwood et al., 2014), since the operational cost (OpEx), which is present in the LCoE formula in (1), is hard to assess due to high level of uncertainty (Astariz and Iglesias, 2015). However, aggressive energy-maximising controllers typically exaggerate device motion (Fig. 1) and produce a strong control force (Fig. 2), which can lead to premature system degradation with a consequent rise in OpEx (Zurkinden et al., 2015, 2013; Windt et al., 2021; Guerrero-Fernandez et al., 2023). Therefore, it is uneconomic to focus only on energy maximising while neglecting adverse control effects on lifetime, leading to higher maintenance costs. Considering the above mentioned facts, there is a need to design *health-sensitive control* for WECs.

The main contribution and objectives of this perspective paper are summarised as follows: Firstly, It provides a general novel basis for future lifetime-aware control studies by formulating the problem and specifying the steps required to reach the best trade-off between captured energy and OpEx through control law modulation. Secondly, it investigates candidate degradation evaluation metrics for lifetime-aware control of WECs by reviewing lifetime studies of WECs and other relevant dynamical systems. Thirdly, it specifies possible challenges in

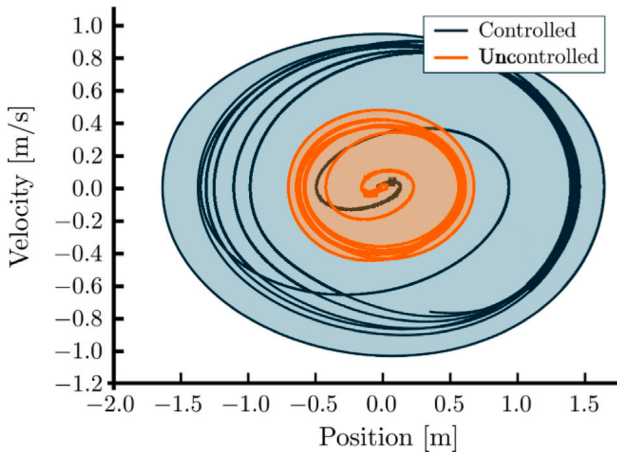

Fig. 1. Operational (phase) space of an uncontrolled and controlled WEC device (Windt et al., 2021).

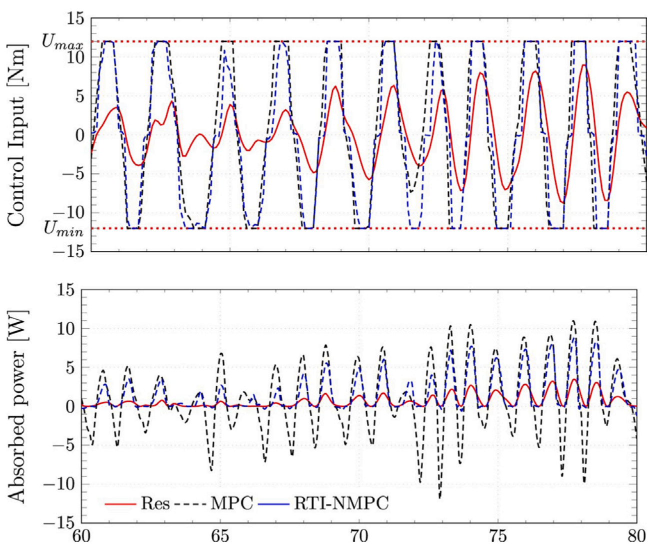

Fig. 2. Control input (PTO force) and absorbed power with different control strategies: model predictive control (MPC), real-time iteration nonlinear model predictive control (RTI-NMPC) and resistive (Res) controller (Guerrero-Fernandez et al., 2023).

longevity control of WECs and gives feasible ideas to address them in future studies.

The remainder of the paper is organised as follows: Section 2 gives a general overview of WEC mathematical modelling. Section 3 defines the lifetime-aware control problem structure, where the goal of the controller is to find a good economic trade-off between the captured energy and OpEx. This section also briefly describes conventional WEC energy-maximising control approaches in the literature. Section 4 investigates how lifetime is assessed and enhanced in various dynamical systems and provides possible metrics for longevity analysis for WECs. Section 5 reviews existing lifetime studies for WECs and classifies them, based on lifetime assessment metrics provided in Section 4. Finally, concluding remarks are given in Section 6, and challenges and possibilities for future research are also discussed.

2. Description of wave energy converters

2.1. Modelling procedure

WECs, as mentioned in Section 1, are devices designed to collect and transform the energy found in ocean waves into useful electrical power.

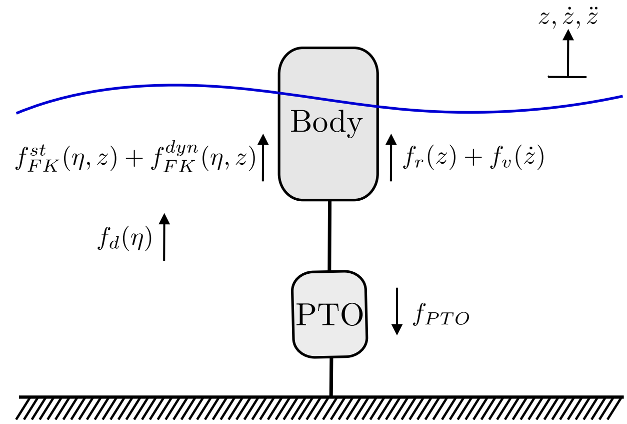

Fig. 3. Simplified illustration of a wave energy converter.

Although WECs come in various forms, and work on different principles to harvest energy from ocean waves (Koca et al., 2013), they can typically be represented in the literature as devices containing floating bodies and power take-off (PTO) systems (actuators). For simplicity, as depicted in Fig. 3, we assume, in the present preliminary analysis, that the floating body can only oscillate in the heave direction (a single degree of freedom), and the resulting body kinetic energy is transformed into electricity through the PTO. The equation of motion for the WEC in Fig. 3 can be obtained by applying Newton's second law as follows (Day et al., 2015; Giorgi and Ringwood, 2018; Giorgi et al., 2016)[1]:

$$m\ddot{z} = f_r(z) + f_v(\dot{z}) + f_d(\eta) + f^{st}_{FK}(\eta, z) + f^{dyn}_{FK}(\eta, z) - f_{PTO}, \tag{3}$$

where z shows the displacement in the heave direction, m is the buoy mass, f_{PTO} is the control force provided by PTO, η is the undisturbed free-surface elevation, $f^{st}_{FK}(\eta, z)$ and $f^{dyn}_{FK}(\eta, z)$ are the static and dynamic Froude–Krylov (FK) forces, f_r is the radiation force, f_d is the diffraction force, and the viscous drag force in the system is represented by f_v.

It is important to note that the motion equation in (3) is unsuitable for control design; hence, the following linear and nonlinear control-oriented models are derived.

2.1.1. Linear time-invariant model

Considering linear potential flow theory (Ringwood et al., 2023), the radiation force f_r in (1) can be written based on the well-known Cummins' equation (Cummins, 1962):

$$f_r = -m_\infty \ddot{z} - \dot{z} * k_r, \tag{4}$$

where added mass at infinite frequency is denoted by m_∞, the radiation impulse response by k_r, and the convolution operator by $*$. In addition, considering $f^{st}_{FK}(\eta, z) = -s_h z$ where s_h is the restoring coefficient constant, we can obtain the following, by substituting (4) into (3) (Giorgi et al., 2016):

$$\begin{cases} M\ddot{z} + k_r * \dot{z} + s_h z = f_{ex} - f_{PTO}, \\ \underbrace{f_{ex} = f_d + f^{dyn}_{FK}}_{\text{Wave excitation force}}, \end{cases} \tag{5}$$

where $M = m + m_\infty$. The term $k_r * \dot{z}$ in (5) makes the calculation of the linear time-invariant parametric state-space model difficult, even though getting a frequency response from (5) is straightforward and can be achieved using a direct Fourier transform (Said et al., 2023b).

[1] Henceforth, the dependency of variables on t will not be shown if it is clear from the context.

As a result, a linear subsystem is regularly used to approximate the radiation damping term (Na et al., 2018; Ringwood et al., 2023):

$$\begin{cases} \dot{x}_r = A_r x_r + B_r \dot{z}, \\ k_r * \dot{z} \approx y_r = C_r x_r + D_r \dot{z}, \end{cases} \tag{6}$$

where $\{A_r, B_r, C_r, D_r\}$ are matrices of appropriate dimension (determined by the order of the approximation), computed using system identification techniques (Pena-Sanchez et al., 2019), and x_r denotes the radiation states. Now, by defining the state vector as $x = [x_1, x_2, x_3] = [z, \dot{z}, x_r]^\intercal$, the linear state-space representation for (5) is expressed as follows:

$$\begin{cases} \dot{x} = Ax + Bu + d, \\ y = Cx, \end{cases} \tag{7}$$

with

$$A = \begin{bmatrix} 0 & -1 & 0_{1\times n_r} \\ -s_h/M & -D_r/M & -C_r/M \\ \mathbf{0}_{n_r\times 1} & B_r & A_r \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ -1/M \\ 0 \end{bmatrix}, \quad u = f_{PTO}$$

$d = Bf_{ex}, \quad C = \begin{bmatrix} 0 & 1 & \mathbf{0}_{1\times n_r} \end{bmatrix}$, and $\quad n_r$: dimension of (6).

2.1.2. Affine nonlinear model

The linear state-space model in (7) is more computationally efficient than a nonlinear model for control design purposes (Papillon et al., 2020), but the model in (7) is based on assumptions related to linear potential flow theory (Ringwood et al., 2023), which can be readily challenged when a controller is connected to the system (Windt et al., 2021). Therefore, it can be advantageous to take into account the primary causes of nonlinearity for relaxing the assumptions (Ringwood et al., 2023). Therefore, considering the linear model in (7) and (3), a more general nonlinear state-space representation is obtained as:

$$\begin{cases} \dot{x} = F(x, \eta) + Bu, \\ y = Cx, \end{cases} \tag{8}$$

where

$$F(x, \eta) = Ax + B(f_v(x_2) + f_d(\eta) + f_{FK}^{dyn}(\eta, x_1)). \tag{9}$$

2.2. Physical constraints

For a control system to operate safely, effectively, and dependably, state (displacement, velocity) and control force constraints must be considered during the control design process (Boyd and Barratt, 1991). This is particularly important in real-world applications where the system needs to conform to regulations and physical constraints. Although unconstrained energy-maximising controllers may provide good insight into control co-design of (say) WEC geometry (Peña-Sanchez et al., 2022), a controller should satisfy the physical constraints after a WEC is designed (i.e., constrained energy-maximising controllers). In other words, designing a controller for a wave energy conversion system without considering the motion and control force constraints does not necessarily achieve the optimum geometry with constrained control (Garcia-Rosa et al., 2015).

The main physical constraints in WECs are mathematically defined as:

$$\begin{cases} |x_1| \le x_{1\,\max}, \\ |x_2| \le x_{2\,\max}, \\ |u| \le u_{\max}, \end{cases} \tag{10}$$

where $x_{1\,\max}$, $x_{2\,\max}$ and $u_{\max}$ are positive scalars representing maximum displacement, velocity, and control force, respectively. It is worth noting that engineers during the WEC design process use data gathered from structural analysis, material properties, and anticipated environmental conditions to define physical constraints; nevertheless, once a device is built, physical constraints cannot be altered (please see Figure 2 in Trueworthy and DuPont, 2020).

3. Control of wave energy converters

To conceive of how health-sensitivity can be incorporated into wave energy control systems, it is crucial that both the control objective, and the generic form of WEC control strategies, be examined, at a broad level of detail. Specifically, regarding the performance objective (Section 3.1), a significant challenge exists in harmonising the relatively long timescales that health-focussed metrics are evaluated on (e.g. years) with the urgency of real-time control decisions (milliseconds). In Section 3.2, the fundamental building blocks of WEC control are established while, in Section 3.3 the basic formulation of optimal WEC control is exposed so that some idea can be given of how health-sensitive WEC control action can be incorporated.

3.1. Control objective

While the primary goal of WEC control is to minimise LCoE, the significant level of uncertainty in OpEx computation makes it challenging to evaluate the LCoE formula in (1) directly. This fact explains why most researchers have only considered maximising captured energy as the primary control goal, ignoring the controller impact on OpEx. Table 1 presents the cost distribution of CapEx to help visualise the issue. It is clear that the control capital cost (i.e. hardware and software development), which is often constant, contributes a relatively small amount to CapEx, and is largely independent of control action. On the other hand, It should be highlighted that O&M is the primary source of uncertainty in OpEx because there is relatively little accessible data on component dependability, failure, and downtime (Astariz and Iglesias, 2016).

Therefore, if we rewrite LCoE in terms of sensitivity to the control action, we have:

$$\mathrm{LCoE_{CS}} = \frac{\mathrm{PV}(\mathrm{CapEx_{CS}}(u)) + \mathrm{PV}(\mathrm{OpEx_{CS}}(u))}{\mathrm{PV}\left(E_c(u)\right)}. \tag{11}$$

$\mathrm{CapEx_{CS}}(u)$ in (11) denotes the capital cost required to generate u, which includes PTO cost and control capital cost (i.e., cost of sensors, software, hardware, and other related expenses), while $\mathrm{OpEx_{CS}}(u)$ denotes expenses directly related to the controller operation. Stated differently, $\mathrm{OpEx_{CS}}(u)$ can be defined as the lifetime degradation cost of the system due to control action (i.e., O & M cost).

Remark 1. It is worth noting that $\mathrm{CapEx_{CS}}(u)$ is considered a constant in the current paper since regular lifetime-aware control structures rely on having a predefined system (i.e., sequential design of a physical system and its control system). However, if $\mathrm{CapEx_{CS}}(u)$ is variable, the problem transfers to a lifetime-aware control co-design problem, involving simultaneous optimisation $\mathrm{CapEx_{CS}}(u)$ and $\mathrm{OpEx_{CS}}(u)$ (Garcia-Sanz, 2019).

So, considering Table 1 and Remark 1, (11) can be rewritten as:

$$\begin{aligned} \mathrm{LCoE_{CS}} &= \frac{\mathrm{PV(Control\ Capital\ Cost{+}PTO\ Cost)} + \mathrm{PV}(\mathrm{OpEx_{CS}}(u))}{\mathrm{PV}\left(E_c(u)\right)} \\ &= \frac{c + \mathrm{PV}(\mathrm{OpEx_{CS}}(\mathrm{u}))}{\mathrm{PV}\left(E_c(u)\right)}, \end{aligned} \tag{12}$$

where c is a positive scalar.

It should be noted that the $\mathrm{LCoE_{CS}}$ in (12) is not a suitable performance function for designing an online optimisation-based controller directly. The reasons for this are:

1. Firstly, controllers have to make decisions fast, often in milliseconds. Therefore, real-time control would not be feasible due to the lengthy processing time needed to calculate $\mathrm{LCoE_{CS}}$ values.
2. Secondly, the $\mathrm{LCoE_{CS}}$ is a single objective function that does not capture all possible trade-offs between $\mathrm{E}_{c(u)}$ and $\mathrm{OpEx_{CS}}(\mathrm{u})$.
3. Finally, it is difficult to calculate $\mathrm{OpEx_{CS}}(\mathrm{u})$, due to the high level of uncertainty.

Table 1
Summary of CapEx for a single WEC (Faraggiana et al., 2020).

	Category	Value
CapEx	Structure cost	43.6% of total CapEx
	PTO cost	30.7% of total CapEx
	Control capital cost	5.3% of total CapEx
	Grid cost	5.2% of total CapEx
	Mooring cost	3.5% of total CapEx
	Installation cost	1.1% of total CapEx
	Margin cost	10.6% of total CapEx

Defining $\mathrm{OpEx}_{\mathrm{CS}}(\mathrm{u}) = f(\chi(u))$ as the output of an unknown function $f(.)$, where $\chi(u)$ reflects the control-sensitive lifetime degradation of the system, minimising control-sensitive operational cost $\mathrm{OpEx}_{\mathrm{CS}}$ can be considered equivalent to minimising the control-sensitive lifetime degradation of the system $\chi(u)$. In other words, $\chi(u)$ relates control actions to special physical effects, such as fatigue, leading to device degradation with a potential consequent increase in $\mathrm{OpEx}_{\mathrm{CS}}$. Hence, the following multi-objective optimisation (MOO) problem (Khezri and Mahmoudi, 2020) can be formulated:

$$\max_u J(x,u) = \left[E_c(u), -\chi(u)\right]^{\mathrm{T}},$$
$$\text{Subject to: } \begin{cases} |x_1| \le x_{1\,\max}, \\ |x_2| \le x_{2\,\max}, \\ |u| \le u_{\max}, \\ \text{linear model (7) or nonlinear model (8).} \end{cases} \tag{13}$$

Fig. 4 shows the required steps needed to be taken to calculate a specific health-sensitive control law. It starts by considering minimising $\mathrm{LCoE}_{\mathrm{CS}}$ at the upper level. Then, minimising $\mathrm{LCoE}_{\mathrm{CS}}$ is mapped to a real-time MOO problem in the lower level by defining the lifetime degradation metric, $\chi(u)$. Finally, after finding all non-dominant optimal solutions (i.e., the Pareto front Emmerich and Deutz, 2018), a multi-criteria decision-making algorithm selects a specific optimal control law.

Remark 2. Degradation can typically be influenced by system variables such as the state vector (x), control input (u), output (y), or external variables such as q (i.e., $\chi(x,y,u,q)$) in (20). Nevertheless, degradation is represented as $\chi(u)$, for the sake of simplicity, in this section, to emphasise that degradation in WECs depends explicitly on the controller operation.

Remark 3. In Fig. 4, steps 3 and 4 show that, after obtaining a Pareto front, an optimal solution is selected based on a multi-criteria decision-making algorithm, such as a Technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) (Ceballos et al., 2016). Each point in the Pareto front represents an optimal value of ($E_c(u)$, $-\chi(u)$) so, considering an unknown function such as $f(.)$, the points can be represented as ($E_c(u), \mathrm{OpEx}_{\mathrm{CS}}(u)$). Therefore, the primary criterion for selecting a point from the Pareto front is $\mathrm{LCoE}_{\mathrm{CS}}$. However, other criteria, such as demand matching, can be considered as an alternative to $LCoE_{CS}$. For example, the points in the Pareto front with higher $E_c(u)$ should be selected when electricity demand is high and a wave source is the only available option within a specific period (Said et al., 2023a). Nevertheless, choosing different criteria is ongoing research, and the current paper only specifies the general structure of WEC lifetime-aware control.

Traditional control techniques (i.e. attempting to minimise LCoE only by maximising E_c) are assessed according to frequency-domain and optimal control classifications in Sections 3.2 and 3.3. Candidates for $\chi(u)$ will be covered in Sections 4 and 5, and Section 6 will address the challenges with the multi-objective optimisation problem in (13).

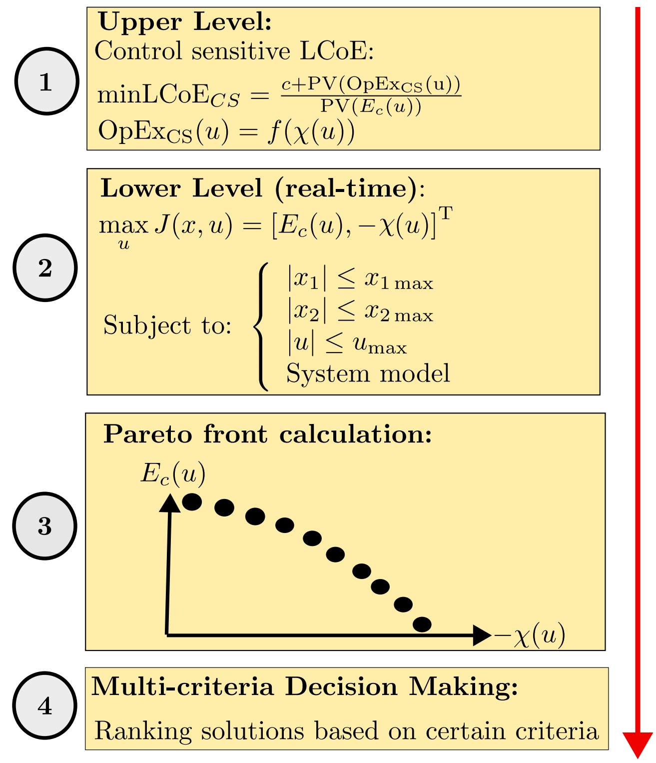

Fig. 4. Structure of health-sensitive control problem.

3.2. Basic WEC control formulation

Non-optimal control methods stem from linear force-velocity models of WECs, typically expressed in the frequency-domain. This implies that if the Fourier transform of (5) is computed, get:

$$j\omega Z(j\omega) = G(j\omega)\left[F_{ex}(j\omega) - F_{PTO}(j\omega)\right], \tag{14}$$

with

$$G(j\omega) = \frac{j\omega}{s_h - \omega^2 M + j\omega K_r(j\omega)}, \tag{15}$$

where $F_{ex}(j\omega)$ is the Fourier transform of $f_{ex}(t)$, $F_{PTO}(j\omega)$ is the Fourier transform of $f_{PTO}(t)$, and $Z(j\omega)$ is the Fourier transform of $z(t)$.

Considering $X_2(j\omega) = j\omega Z(j\omega)$, $U(j\omega) = F_{PTO}(j\omega)$ and defining the intrinsic impedance with $Z_{imp}(j\omega) = G(j\omega)^{-1}$, (14) can be written as:

$$X_2(j\omega) = \frac{F_{ex}(j\omega) - U(j\omega)}{Z_{imp}(j\omega)}. \tag{16}$$

Then, a proportional controller can be defined as $U(j\omega) = Z^u_{imp}(j\omega)X_2(j\omega)$, where $Z^u_{imp}(j\omega)$ represents the control load (impedance). Consequently, (16) can be rewritten as:

$$X_2(j\omega) = \frac{1}{Z_{imp}(j\omega) + Z^u_{imp}(j\omega)} F_{ex}(j\omega). \tag{17}$$

Now, (17) can be represented as an electrical circuit (Fig. 5). Therefore, according to the impedance-matching concept, $U(j\omega)$ maximises the performance function (2) if the control impedance is constructed as follows (Korde and Ringwood, 2016):

$$Z^u_{imp}(j\omega) = Z^*_{imp}(j\omega), \tag{18}$$

where $Z^*_{imp}(j\omega)$ represents the complex-conjugate of $Z_{imp}(j\omega)$.

The simple complex-conjugate feedback controller (i.e. $U(j\omega) = Z^u_{imp}(j\omega)X_2(j\omega)$) has some significant disadvantages (García-Violini et al., 2020a; Ringwood et al., 2023): (a) the feedback controller is frequency-dependant, meaning each frequency needs a specific optimal

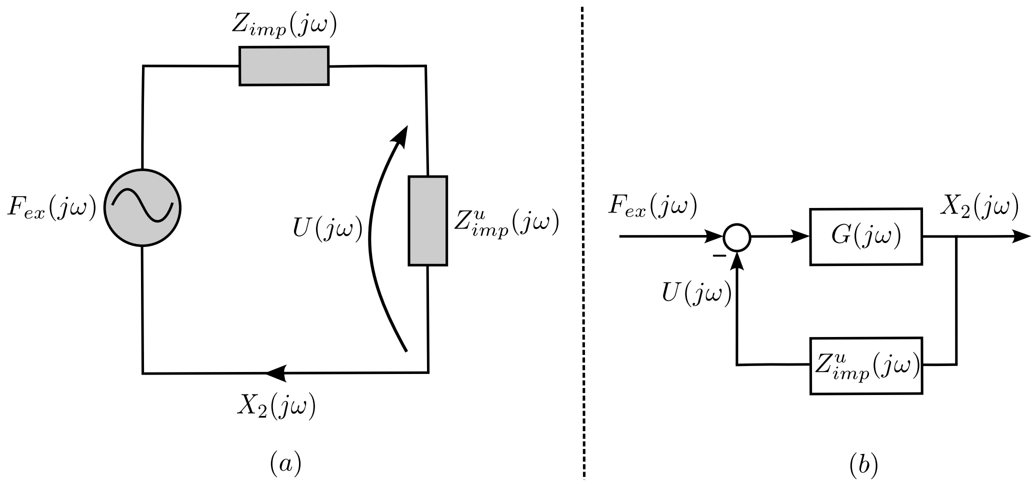

Fig. 5. (*a*) Equivalent circuit of impedance-matching problem. (*b*) Impedance-matching control structure.

impedance; (b) due to the non-casual behaviour (Scruggs, 2010) of the feedback controller, its real-time implementation is infeasible for panchromatic waves i.e. the closed-loop system (see Fig. 5) is unstable.; and (c) the controller cannot handle constraints. However, some frequency-domain WEC controllers can handle the problems mentioned for the simple feedback controller (García-Violini et al., 2020a). Frequency-domain controllers can be classified into feedforward and feedback mechanisms. WEC feedback controllers can furthermore be divided into velocity tracking controllers (Fusco and Ringwood, 2012, 2011), in which reference velocity is generated by wave excitation force estimation, and regular feedback controllers, which do not require the estimation of the wave excitation force (Song et al., 2016; Bacelli et al., 2019). On the other hand, feedforward controllers use an estimate of wave excitation force as a direct input to the energy-maximising controller (García-Violini et al., 2020b). Although frequency-domain controllers are less complex, they are limited to operating on an approximate linear model and require an additional mechanism to satisfy input or state constraints.

3.3. Optimal control strategies

Optimal WEC controllers use the optimal control principles to maximise absorbed energy, compared to conventional optimal control methods used for setpoint tracking. Generally, optimal control involves solving a mathematical optimisation problems to find admissible optimal control actions that lead to desired outcomes, while satisfying system dynamics and constraints (Lewis et al., 2012). The optimal control problem for a WEC is defined as:

$$\begin{cases} max \quad E_c, \\ \text{subject to :} \\ \text{linear model (7), or nonlinear model (8),} \\ |x_1| \le x_{1\,\max}, \\ |x_2| \le x_{2\,\max}, \\ |u| \le u_{\max}. \end{cases} \tag{19}$$

Model predictive control (MPC) (Li and Belmont, 2014; Nguyen et al., 2016; Hansen et al., 2019), spectral optimal control (Bacelli and Ringwood, 2014) and moment-based control methods (Faedo et al., 2019) are examples using a similar structure to (19), and have been applied to wave energy systems (Faedo et al., 2017; Ringwood et al., 2023). The main benefit of optimal control methods is that constraints are satisfied while computing the optimal control law, via the use of constrained optimisation algorithms. Moreover, they can be extended for nonlinear WEC models (Faedo et al., 2022a,b; Guerrero-Fernandez et al., 2023). However, all these advantages come at the expense of increased complexity in the control algorithm (discretisation techniques for real-time implementation, large number of tunable parameters, advanced hardware requirements, etc.) and uncertainty in convergence, as the degree of nonlinearity and complexity of the constraint set grows (Ringwood et al., 2023; Faedo et al., 2020).

4. Lifetime analysis in control systems

In this section, the lifetime in control systems is analysed based on the well-known primary metric: Degradation, in Section 4.1. Despite the fact that reliability and remaining useful life (RUL) provide some means for representing degradation, they are investigated separately in Sections 4.2 and 4.3, due to their broad use in the literature.

4.1. Degradation

Degradation is the primary metric utilised in the literature to characterise system lifetime. Degradation, in general, is the gradual loss of functionality of a system, which can result in failure (McPherson et al., 2010). Even though different degradation path models can be followed for various types of degradation (Meeker et al., 2014), Fig. 6 illustrates a basic convex degradation path model, separated into three separate regions. The system is not significantly impacted by degradation in the low-impact period ($0 < t < t_0$). However, after t_0, degradation can be seen in the system, or the system is in a deteriorated condition. The degradation continues until t_1, reaching its maximum value, χ_1. Then, the system enters the failure period due to a failure occurrence. The degraded system between $t_0 < t < t_1$ can be mathematically described by considering the following state-space model:

$$\begin{cases} \dot{x} = F_1(x, u, \chi), \\ y = F_2(x, u, \chi), \\ \chi = F_3(x, y, u, q), \end{cases} \tag{20}$$

where F_1, F_2 and F_3 are general non-linear functions, q shows the independent variables from the model of the system (i.e. disturbance).

Therefore, considering (20), degradation can be divided into the following four distinct classifications (Zagorowska et al., 2020): Model-based factor-dependent degradation (Section 4.1.1), model-free factor-dependent degradation (Section 4.1.2), model-based factor-independent degradation (Section 4.1.3), and model-free factor-independent degradation (Section 4.1.4).

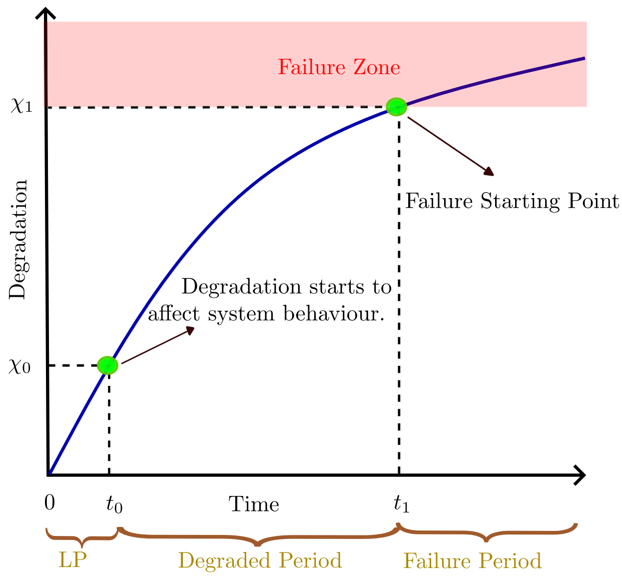

Fig. 6. An example of a convex degradation path model, which is divided into three distinctive periods: Low-impact degradation period (LP), degraded period, and failure period.

4.1.1. Model-based factor-dependant degradation (MB+FD)

In MB+FD, the deterioration depends on system variables such as x, y, and u, in addition to being visible in the state-space representation of the system, (20). For example, in Suri and Onori (2016), the degradation of a Lithium-ion battery of a hybrid electrical vehicle is considered. The degradation model of the battery is constructed based on system variables such as internal temperature, state of charge, and current. In addition, the system behaviour is affected based on the degradation. Finally, the degradation is minimised alongside the instant consumption fuel rate by defining a multi-objective optimal control problem.

4.1.2. Model-free factor-dependent degradation (MF+ FD)

Despite the awareness of the system variables influencing the degradation model in MF+FD, it is difficult to comprehend how deterioration modifies the behaviour of the system in the degraded state shown in Fig. 6. The mathematical representation of MF+FD can be obtained from the system (21) as:

$$\begin{cases} \dot{x} = F_1(x, u), \\ y = F_2(x, u), \\ \chi = F_3(x, y, u, q). \end{cases} \tag{21}$$

An example of MF+FD degradation is illustrated in the case of wind turbines, where it is challenging to see the blade crack propagation effect on the system model until a failure happens. The fatigue of wind turbine blades, as a source of degradation, is analysed in Sanchez et al. (2018). The degradation model (i.e., the accumulated fatigue damage), which is a function of disturbance, control signal, and system state, is determined using the rainflow counting method (Niesłony, 2009) and the Palmgren–Miner rule (a deterioration path model to describe fatigue) (Miner, 2021). Ultimately, the accumulated damage is minimised by adding it to the MPC performance function.

4.1.3. Model-based factor-independent degradation (MB+ FI)

In MB+FI, the system variables (x, y, and u) are not the basis of the degradation process; instead, the degradation effect is discernible in the behaviour of the system. Degradation is therefore defined as a function of external factors such as q, a stochastic metric, or a constant value in different periods. For instance, the degradation model for valve deterioration in McGhee et al. (2014) is based on a diminishing pipe area. It is formulated as a stochastic process, with its effect discernible in the output pressure. Another example is the lifespan regulation of micro-gas turbine engines in Zaccaria et al. (2020). Degradation alters the turbine inlet temperature, a system variable, piecewise constant.

4.1.4. Model-free factor-independent degradation (MF+ FI)

In MF+FI, the degradation model is factor-free and degradation is not visible in the system behaviour. Less often employed in control systems, MF+FI is commonly utilised in prognostics and maintenance planning by using metrics such as remaining useful life (Mosallam et al., 2016) and reliability (Rausand and Hoyland, 2003). In other words, these metrics evaluate the critical component state and schedule necessary maintenance activities before failure.

4.2. Reliability

System or component reliability is its ability to carry out its intended tasks, under given circumstances, for a predetermined amount of time. It also can be defined as the probability that the system does not fail until t_1 in Fig. 6, and is mathematically described (Rausand and Hoyland, 2003) as:

$$R(t) = e^{-\int_0^t \lambda(t)dt}, \tag{22}$$

where $\lambda(t)$ is the failure rate (number of failures in per unit of time). In the literature, reliability has mostly been used to describe degradation when it belongs to the MF+FD (Section 4.1.2) or MF+FI (Section 4.1.4) categories.

4.3. RUL (remaining useful life)

RUL is the estimated time that machinery or equipment can be used before suffering a major failure. We can write (Nguyen et al., 2015), using Fig. 6,

$$RUL(t) = t - t_1, \tag{23}$$

where $t_0 \le t < t_1$. In MF+FI, RUL is predicted to give an alarm before failure; however, in other categories, it can be used to design a control law based on the RUL tracking error. For example, in Rodriguez et al. (2018), the degradation effect is compensated by designing an optimal control law, minimising the RUL tracking error in a friction drive system. Relevant articles in the literature are categorised in Table 2 according to the research application and degradation type. Additionally, it indicates which metrics such as reliability, degradation model, and RUL are applied to lifetime analysis, and makes it clear whether these measures are utilised for lifetime-aware control design.

5. Lifetime studies in wave energy converters

Recognising the factors that impact the lifespan of WECs is crucial for optimising their design, operation, and maintenance, ultimately paving the way for a more reliable and cost-effective wave energy industry. Section 5 starts by investigating the various physical and environmental factors that can contribute to the degradation and eventual failure of WECs (Section 5.1). Then, the degradation of control-related factors is evaluated in Section 5.2. Finally, the existing health-sensitive control approaches in the WECs literature are studied in Section 5.3.

5.1. Factors affecting the lifetime of WECs

Sections 5.1.1 and 5.1.2 introduce the factors contributing to lifetime degradation of WECs. These factors can be classified based on the controller operation in two categories: non-control related deterioration factors (Corrosion and biofouling in 5.1.1) and control-related ones (cyclic loading in 5.1.2).

Table 2
Articles in the area of lifetime analysis of control systems.

Reference	MB+FD	MF +FD	MB+FI	MF +FI	Application	Working metric	Control
Suri and Onori (2016), Sezer (2019) and Hou et al. (2023)	✓				Hybrid electrical vehicle	Degradation model	✓
Nasiri et al. (2023)		✓			All-electric ship	Degradation model	✓
Nasiri et al. (2021)		✓			All-electric ship	Degradation model	✗
Ju et al. (2022)	✓				Electrical vehicle	Degradation model	✓
Niu and Jiang (2017)	✓				Braking system of rail vehicles	Degradation model	✓
McGhee et al. (2014)			✓		Valve degradation within power stations	RUL	✗
Zaccaria et al. (2020)			✓		Microgas turbine	Degradation model	✓
Niu and Jiang (2017)	✓				Braking system of rail vehicles	Degradation model	✓
Gong et al. (2023) and Huynh et al. (2017)	✓				Linear time-invariant systems	RUL	✗
Niu and Jiang (2017)	✓				Braking system of rail vehicles	Degradation model	✓
Karimi Pour et al. (2019)		✓			Water transport network	Reliability	✓
Verheyleweghen et al. (2018)		✓			Subsea compression system	Degradation model	✓
Langeron et al. (2017)	✓				Linear time-invariant systems	RUL	✓
Pereira et al. (2010) and Gong et al. (2021)	✓				Linear time-invariant systems	Degradation model	✓
Pour et al. (2018)		✓			Pasteurisation pilot plant	Degradation model	✓
Salazar et al. (2017), Chamseddine et al. (2014) and Zhang et al. (2022)		✓			Linear time-invariant systems	Reliability	✓
Sanchez et al. (2016) and Butler et al. (2012)				✓	Wind turbines	RUL	✗
Sanchez et al. (2018, 2015) and Njiri et al. (2019)		✓			Wind turbines	Degradation model	✓
Abdelmoumene and Bentarzi (2023)				✓	Wind turbines	Reliability	✗
Rodriguez et al. (2018) and Obando et al. (2021)	✓				Friction drive system	RUL	✓
Mosallam et al. (2016)				✓	Unknown system	RUL	✗
Tsoumpris and Theotokatos (2022)		✓			Ship hybrid power plants	Reliability	✗
Pour et al. (2021)		✓			Racing vehicles	RUL	✓
Moulahi and Ben Hmida (2022)			✓		Nonlinear systems	RUL	✗

5.1.1. Corrosion and biofouling

In this section, non-control related degradation factors are discussed, where the degradation is independent of controller operation.

Materials used in WECs progressively degrade when exposed to the sea environment (e.g. corrosion, biofouling, etc.). Variations in water temperature and pH are some of the elements that frequently contribute to corrosion (Hudson et al., 1980). Generally, choosing suitable materials and coatings can reduce corrosion in WECs (Oikonomou and Aggidis, 2021).

Among the non-control related factors, bio-fouling has gained a lot of interest among researchers in the marine sector due to complexity in modelling this natural process (Romeu and Mergulhão, 2023). Biofouling can be defined as the growth of microorganisms, vegetation, and other marine life on a surface in contact with water. In maritime systems, biofouling is typically mitigated by underwater cleaning robots (Ohrem et al., 2021), acoustic approaches, or anti-fouling coating (Legg et al., 2015). When taking WECs into account, biofouling may have an impact on submerged system components, such as power cables and mooring lines (see Fig. 7). Mooring line and power cable biofouling, for instance, are simulated as increases in the mass and drag coefficients of the lines in Yang et al. (2017b). It was demonstrated that biofouling could decrease power absorption by 10% and mooring line fatigue life by about 20% in a WEC.

5.1.2. Cyclic loading

The viability and long-term sustainability of WECs are intrinsically linked to their ability to withstand the harsh environment they operate in. One of the primary challenges in this regard is **fatigue due to cyclic loading** (Zurkinden et al., 2015, 2013; Nielsen et al., 2017). Generally, fatigue is the gradual weakening and eventual failure of a material due to repeated cycles of stress or loading. It occurs at the microscopic level, where cracks initiate and grow within the material under repeated stress (Shigley et al., 2011). The cyclic loading in WECs is due to hydrodynamic forces (wave load) and PTO forces. This is apparent if (3) is rewritten as:

$$m\ddot{z} = f_{hydro}(z, \dot{z}, \eta) - f_{PTO}, \tag{24}$$

where

$$f_{hydro}(z, \dot{z}, \eta) = f_r(z) + f_v(\dot{z}) + f_d(\eta) + f^{st}_{FK}(\eta, z) + f^{dyn}_{FK}(\eta, z). \tag{25}$$

Therefore, considering Fig. 1 and Eq. (24), it is evident that aggressive controllers not only cause significant stress by generating intense PTO forces but also result in significant wave loads $f_{hydro}(z, \dot{z}, \eta)$ due to motion exaggeration. Sections 5.2 and 5.3 will investigate how degradation due to cyclic loading is analysed and mitigated through control theory in the literature.

5.2. Lifetime assessment of WECs

From Section 5.1, we know cyclic loading is the fundamental reason for the device degradation due to the interaction of all forces present in the dynamical model of system (24). However, the question is: How is it possible to assess the effect of cyclic loading on system lifetime? Generally, the adverse effect of cyclic loading is calculated as accumulated damage (a physical knowledge-based degradation model) (Muñiz-Calvente et al., 2022). Fig. 8 shows that accumulated fatigue damage can be computed in the time or frequency domains (Martinez-Puente et al., 2023). The fatigue assessment process begins with evaluating the material fatigue characteristics. Therefore, for a specific fatigue indicator parameter such as stress, the fatigue life model of the material is obtained (i.e. the reference S–N curve Wöhler, 1870). Then, the loading history, such as the stress-time signal, is calculated for a specific component by a numerical (e.g. finite element analysis Bhavikatti, 2005) or experimental method, considering the loads and geometry

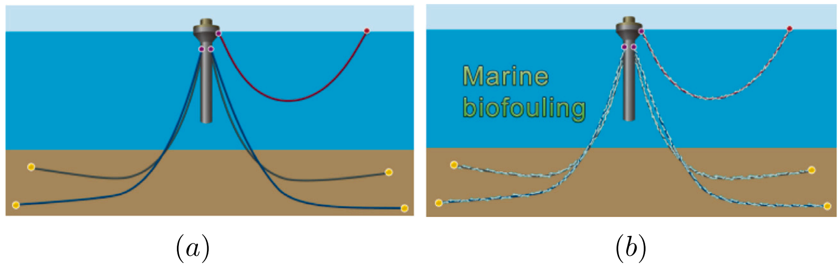

Fig. 7. Schematic of a WEC (*a*) when there is no biofouling in mooring lines (in blue colour) and power (in red colour) cable, and (*b*) when biofouling is present (Yang et al., 2017a).

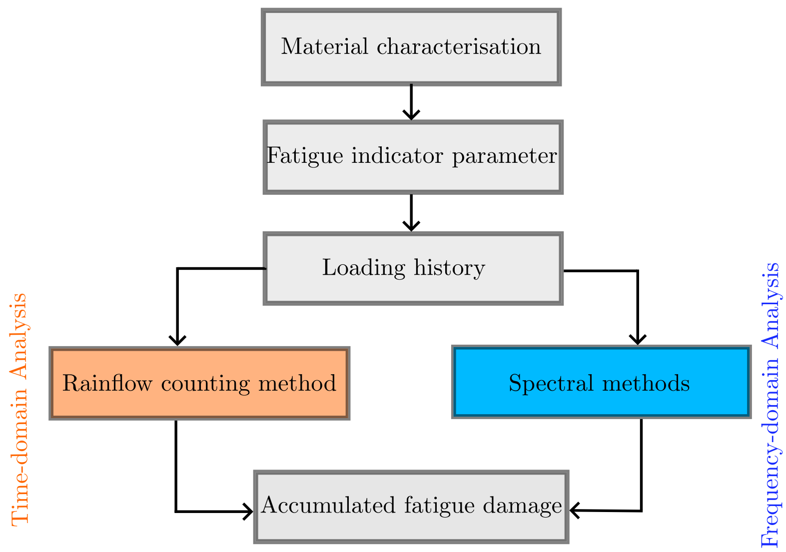

Fig. 8. The flowchart of fatigue assessment (Muñiz-Calvente et al., 2022).

associated with a component. Following calculation of the loading history, the loading history is transformed into loading history by cycles (e.g. a stress-cycle graph Ferri et al., 2014) due to the complexity of recording all the history data in the time or frequency domains. This transformation is done by the rainflow counting method in the time domain or similar spectral (frequency-domain) methods, such as the narrow band method (Martinez-Puente et al., 2023; Paduano et al., 2024). Finally, accumulated damage is obtained based on the Palmgren–Miners equation (Miner, 2021) in the time domain, or a probability density function (PDF) in the frequency domain (Muñiz-Calvente et al., 2022). Examples of frequency-domain and time-domain methods for WECs are gathered in Table 3.

In addition to studies that consider accumulated damage as a mathematical model of degradation (i.e. $\chi(.)$), some studies, such as Kolios et al. (2018) and Liu et al. (2019), represent degradation in WECs as a reliability function. However, reliability assessment, different from the reliability function in (4.2), is probabilistic. In general, probabilistic reliability is used when there is no specific data for the failure rate of a component. Hence, reliability is defined as failure probability based on the reliability index (β) of the most probable failure point (Ambühl et al., 2015):

$$P_f = \Phi(-\beta), \tag{26}$$

where the $\boldsymbol{\Phi}$ is the standard normal distribution function.

5.3. Lifetime-oriented control of WECs

Unfortunately, the lifetime-aware control problem is not well established for WECs, compared to other renewable systems. In other words, there are very few studies in the literature discussing the trade-off between captured energy and system degradation through control theory with constant CapEx (Hillis et al., 2021; Tom et al., 2016; Hoffmann et al., 2023; Yetkin et al., 2021), in contrast to the majority of papers attempting to reach the best possible trade-off by only redesigning the system structure (varying CapEx), without designing a lifetime-aware controller (Ferri et al., 2014; Nielsen et al., 2017). Most existing lifetime-aware control methods have studied this problem by defining penalty factors on the system states ($\boldsymbol{x}$) or control inputs ($\boldsymbol{u}$) in an optimal control structure (Hillis et al., 2021; Tom et al., 2016; Yetkin et al., 2021). For example, the accumulated fatigue damage of mooring and PTO lines is considered in Hillis et al. (2021), where the trade-off between absorbed energy and fatigue is investigated by simulating for different $\boldsymbol{Q}$ matrix values in the optimal control performance function (i.e. $\int_0^\infty \left(\mathbf{y}^T\mathbf{Q}\mathbf{y} + \mathbf{u}^T\mathbf{R}\mathbf{u}\right)\mathrm{d}t$). A similar method is presented in Tom et al. (2016); where a penalty weight for control torque magnitude for balancing fatigue and captured energy in an oscillating surge WEC is introduced. In addition, the study in Liao et al. (2024) uses unconstrained speed-limiting and energy-maximising MPC algorithms for an attenuator WEC with a permanent magnet synchronous generator (PMSG) to reduce PTO shutdowns in higher sea states, leading to increased OpEx and shorter lifetime. However, Liao et al. (2024) does not evaluate and control WEC lifetime directly; in other words, it is not in the spirit of the optimal control structure in Fig. 4. The automatic switching mechanism between control stages in Liao et al. (2024) could lead to non-operational periods and increased wear, relying heavily on an ideal wave predictor performance. The lack of a lifetime-aware control structure may also increase degradation in small to moderate sea states, despite infrequent velocity constraint violations, since lifetime can still be decreased by control input exaggeration (Figs. 1 and

Table 3
Classification of articles in the area of lifetime analysis and lifetime-aware control of WECs, where FDAD and TDAD are accumulated damage (frequency-domain) and accumulated damage (time-domain), respectively.

Reference	Metric	WEC type	Degrading component	Control
Nielsen et al. (2017)	TDAD	Point absorber	Hydraulic cylinder shaft	✗
Shao et al. (2023)	TDAD	Point absorber	Mooring lines	✗
Arredondo-Galeana et al. (2023)	FDAD	Wave cycloidal rotor	Hydrofoils	✗
Zurkinden et al. (2013)	FDAD	Point absorber	Joint of the cylinder and the arm	✗
Zurkinden et al. (2015)	FDAD	Point absorber	The complete wavestar arm	✗
Ferri et al. (2014)	TDAD	Point absorber	Welded connections on the hydraulic cylinder	✗
Ewart et al. (2017)	TDAD	Albatern 12S	Link arm	✗
Hillis et al. (2021)	TDAD	WaveSub	Mooring lines	✓
Arredondo-Galeana et al. (2022)	TDAD	Wave cycloidal rotors	Hydrofoil	✗
Hoffmann et al. (2023)	TDAD	Dielectric elastomer	Dielectric elastomer generator	✓
Tom et al. (2016)	TDAD	Oscillating surge	Flap	✓
Kolios et al. (2018)	Reliability	Point absorber	Floater	✗
Liu et al. (2019)	Reliability	Water hydraulic drive	Blade system	✗

2). In contrast to the aforementioned methods, relying on a numerous number of fatigue simulations, with different control parameters in every run to find suitable values, in Hoffmann et al. (2023), a lifetime-aware control method for dielectric elastomer WECs is presented in the general multi-objective optimisation (MOO) structure, given in (13), where the degradation model is only dependant on the applied voltage (control input) and occurs when degradation reaches a certain value, break-down of the electrical field occurs. It is worth mentioning that electrical cyclic loading in Hoffmann et al. (2023) is a simplified version of cyclic loading in (24), where f_{PTO} is interpreted as the applied voltage of the generator, and f_{hydro} is neglected. Therefore, there is still a gap in the literature for developing a comprehensive lifetime-aware control method for WECs in the structure shown in Fig. 8.

Section 5 ends with Fig. 8, which summarises available lifetime studies in the literature (Sections 5.2 and 5.3). It can be seen that the majority of papers evaluate degradation by calculating accumulative fatigue damage, which is an inherently factor-dependant (FD) model (i.e., cyclic loading is the result of the interaction of forces in (24)); however, it is challenging to show the effect of fatigue (i.e., crack propagation due to cyclic loading) on system behaviour. Therefore, degradation assessment for WECs is MF+FD (see Section 4) based on accumulated fatigue damage, similar to wind turbines (Sanchez et al., 2018, 2015; Njiri et al., 2019).

6. Conclusions and perspectives

It is undeniable that the energy in ocean waves represents a free and abundant energy source, offering a promising option to mitigate the effects of anthropogenic climate change. However, the technology for capturing this energy in waves comes with a price. One of the key, well-known, metrics in the literature which describes the cost of harnessing wave energy is LCoE (Guo and Ringwood, 2021a). In recent decades, control-theory researchers have interpreted the minimisation of LCoE as the maximisation of captured energy. However, this is not true in the bigger picture, considering the potential conflict between energy maximisation and its deleterious effects on OpEx. This relatively short-sighted view among researchers mainly stems from the complexity of showing the relation between OpEx and real-time control laws. Therefore, there is an emerging need to develop health-sensitive controllers for WECs.

The essence of the lifetime-aware control problem is finding a suitable trade-off between maximising energy and minimising maintenance costs, by modulating the control law, assuming a fixed amount of CapEx.[2] In other words, with an initial outlay of funds, the desire is to make the most of wave devices, but not at the expense of overly exaggerated motion, leading to lifetime degradation with consequent increases in OpEx.

Although this review paper offers foundations for health-sensitive control of WECs, future research should look into the following rising challenges:

- The first challenge is the need for a degradation model. For WECs, based on the physics of the system, it is known that degradation (accumulated fatigue damage, reliability and RUL) is dependent on the system variables, such as the control force (f_{PTO}) and the motion of the system (z, $\dot{z}$); however, these parameters are usually absent in the final formula of the accumulated damage and reliability in the studies reported in Table 3. Therefore, in the first step, the degradation should include system variables, especially the control input (u), similar to the approach for wind turbines (Sanchez et al., 2018, 2015; Njiri et al., 2019).
- The second challenge is that degradation (fatigue) is usually evaluated over a long time frame, usually on a yearly basis, so it needs to be effectively calculated in real-time, to mitigate its effects through the control law. This problem can be investigated by dividing fatigue calculations into short-term and long-term effects (Zurkinden et al., 2013; Paduano et al., 2024).
- The third challenge is the necessity to reconstruct the LCoE formula based on degradation cost. For example, in Ferri et al. (2014), the cost of fatigue is interpreted as the cost of requirements for increased dimensions of the structure (co-design); however, for the lifetime-aware control problem, the opposite interpretation should be obtained as reformulating the LCoE calculation, based on the cost of maintenance due to control actions (i.e. $OpEx_{CS}(u) = f(\chi(u))$).
- Finally, there is a need for a multi-criteria decision-making algorithm to rank the solution of the Pareto front to design control laws to reach the best economic trade-off between fatigue and absorbed energy.

CRediT authorship contribution statement

Amin Ziaei: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Conceptualization. **Hafiz Ahsan Said:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Conceptualization. **John V. Ringwood:** Writing – review & editing, Visualization, Supervision, Methodology, Investigation, Conceptualization.

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.

[2] Note that considering variable value for CapEx, transforms the problem to a co-design problem, which is not the focus of this review paper.

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