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Health aware control of wave energy converters: Possibilities and challenges

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ABSTRACT: Wave energy converters are devices that convert the kinetic and potential energy of waves to electricity. Although wave energy devices show promise in meeting the world's energy needs, they currently have a lower technology readiness level (TRL) than their solar and wind counterparts, resulting in a higher levelised cost of energy (LCoE). Therefore, LCoE is the primary performance function to be minimised, but LCoE is relatively complex to be calculated directly, particularly considering the high level of uncertainty in operational costs (OpEx). Accordingly, control researchers have, to date, considered captured energy as a surrogate performance function for LCoE since absorbed energy is a more direct and measurable control objective. Nevertheless, the energy-maximising controllers deleteriously affect the device lifetime, leading to an increase in OpEx. This paper aims to find possible ways to compensate for the adverse effects of energy-maximising controllers on OpEx by considering lifetime metrics such as accumulated fatigue damage, reliability and remaining useful life (RUL) in the controller design process in order to reach an acceptable trade-off between captured energy and device lifetime. The obstacles and opportunities for future research will also be covered.

1 INTRODUCTION

As deposits of fossil fuels diminish, and concern rises over climate change, humankind looks at alternatives, such as renewable energies. Renewable energy resources are essential to our future since they are abundant and naturally replenished. One such renewable energy resource is ocean waves with a huge untapped potential to provide energy, amounting to 32,000 TWh/year globally (Reguero et al. 2015). Wave energy converters (WECs) are the devices to harness wave energy, and there are hundreds of WEC prototypes reported in the literature (Ringwood et al. 2023). The wave energy industry is still in its infancy, with WECs lagging behind other renewable energy technologies, such as wind turbines, in terms of their technology readiness level (TRL) (Guo & Ringwood 2021) and higher levelised cost of energy (LCoE). In this regard, the development of WEC control technology is viewed crucial for enhancing the economic feasibility of wave energy projects by reducing their LCoE.

LCoE is usually defined over a project lifetime (in years) as (Ringwood et al. 2023):

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

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 & 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 absorbed power:

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

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

The problem with considering LCoE as a performance function is that LCoE is not calculated in real-time, while controllers have to operate in real-time. Secondly, there is a high level of complexity in the LCoE calculation itself, considering the substantial uncertainty in OpEx evaluation (Astariz & Iglesias 2015). As a result, control researchers use maximum captured energy as a *surrogate* measure of minimum LCoE (Ringwood et al. 2023), operating exclusively on the denominator of (1). However, energy-maximising WEC controllers exaggerate the device motion, as illustrated in Figure 1, which may have an adverse effect on the device longevity. Consequently, the exaggerated device motion may lead to lifetime degradation and consequent increases in OpEx (Zurkinden et al. 2015). Hence, it is crucial to include a metric for assessing the adverse effects of the controller into the WEC control formulation to enhance device lifetime.

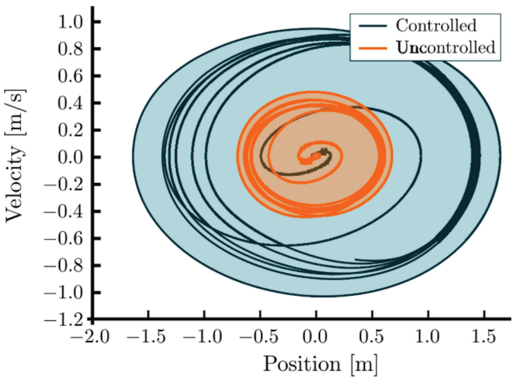

Figure 1. Operational (phase) space of an uncontrolled and controlled WEC device (Windt et al. 2021).

Generally, there can be two distinct ways to reduce adverse effects of the controller on the device lifetime: redesigning (robustifying) the system (increasing CapEx) and lifetime-aware control (constant CapEx). In the first approach, a device is built strongly enough to withstand lifetime degradation, whereas the control input modulation enhances the device lifetime in the second approach, though with a possible penalty on power production. In the literature, many papers consider redesigning a WEC to reach a longer lifetime (Ferri et al. 2014, Nielsen et al. 2017), but little attention is paid to lifetime-aware control (Hoffmann et al. 2023). Lifetime-aware control is important since upgrading or changing a component to reach a specific lifetime level is not economic when a simple control law modulation may result in the same result. Redesigning the system is only needed when it is impossible to enhance the lifetime by control law modulation. Designing a lifetime-aware WEC controller presents challenges, particularly concerning the time scales associated with OpEx, typically calculated over lifetime of the device, and control, usually in real-time. Hence, there is a need to address these challenges by defining a *sensible* objective function and reconciling time-scale issues.

To this end, the main contribution of this paper is to define the lifetime-aware control structure for WECs and to find a lifetime-aware surrogate measure of LCoE in real-time with the help of possible lifetime evaluation metrics, such as accumulated fatigue damage (Muñiz-Calvente et al. 2022), reliability (Rausand & Hoyland 2003) and remaining useful life (RUL) (Kim et al. 2017).

The remainder of the paper is as follows: Section 2 gives a general overview of WEC mathematical modelling. Section 3 defines the lifetime-aware control problem structure, while Section 4 investigates possible real-time metrics for degradation description. Section 5 discusses the pros and cons of the proposed degradation descriptions. Finally, concluding remarks are given in Section 6.

2 WEC MODELLING

Without the loss of generality, the motion of a WEC, for single-degree-of-freedom, can be written in the body-fixed frame using Newton's second law as follows (Faedo et al. 2022) and (Giorgi & Ringwood 2017) (Henceforth, the dependency of variables on t will not be shown if it is clear from the context.):

$$m\ddot{z} = f_{hydro}(z, \dot{z}, \eta) - f_{PTO}, \tag{3}$$

where z and $\dot{z}$ are the displacement and velocity of the device, η is the undisturbed free-surface elevation, f_{PTO} is the control force, provided by a power take-off (PTO), and f_{hydro} is the superposition of all hydrodynamic forces, interacting with the device depicted in Figure 2.

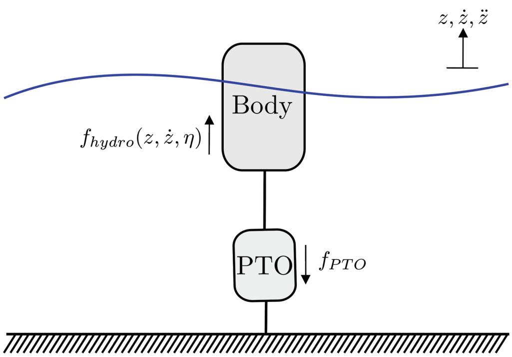

Figure 2. Simplified illustration of a wave energy converter, operating in a single (heave) degree of freedom.

To obtain a state-space representation for (3), one can propose a state vector $x = [x_1, x_2]^{\mathrm{T}} = [z, \dot{z}]^{\mathrm{T}}$, alongside a control input as $u = f_{PTO}$. As a result, the general non-linear state-space model is written as:

$$\begin{cases} \dot{x}_1 = x_2, \\ \dot{x}_2 = f_{hydro}(x_1, x_2, \eta) - u, \\ y = x_2, \end{cases} \tag{4}$$

where y represents the system output.

Furthermore, the main physical constraints in WECs are mathematically defined (Faedo et al. 2017) as:

$$\begin{cases} |x_1| \leq x_{1\,\max}, \\ |x_2| \leq x_{2\,\max}, \\ |u| \leq u_{\max}, \end{cases} \tag{5}$$

where $x_{1\,\max}$, $x_{2\,\max}$ and $u_{\max}$ are positive scalars representing maximum displacement, velocity, and control force, respectively.

3 HEALTH SENSITIVE CONTROL PROBLEM FORMULATION

The essence of a 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. Therefore, the LCoE in (1) can be rewritten explicitly recognising terms sensitive to the control action, u:

$$\mathrm{LCoE_{CS}} = \frac{\mathrm{CapEx} + \mathrm{PV}(\mathrm{OpEx_{CS}}(u))}{\mathrm{PV}(E_c(u))}, \tag{6}$$

where $\mathrm{LCoE_{CS}}$ is the part of LCoE which is sensitive to u, $\mathrm{OpEx_{CS}}(u)$ denotes operational expenses directly related to the controller operation. It should be noted that CapEx in (6) is assumed as a constant (i.e. $\mathrm{CapEx} = c$, c is a positive scalar).

It is worth noting that $\mathrm{LCoE_{CS}}$ is not calculable in real-time; hence, a new performance function such as J in (7) is defined as an alternate measure of $\mathrm{LCoE_{CS}}$ in real-time for designing a lifetime-aware controller. Therefore, the following multi-objective optimisation (MOO) problem (Khezri & Mahmoudi 2020) based on J can be formulated as:

$$\begin{aligned} &\max_u J(x,u) = [E_c(u), -\chi(u)]^{\mathrm{T}}, \\ &\text{Subject to}: \begin{cases} \text{the system model}\,(4), \\ \text{the physical constraints}\,(5), \end{cases} \end{aligned} \tag{7}$$

where $\chi(u)$ is degradation.

The multi-objective performance function J is a better interpretation of $\mathrm{LCoE_{CS}}$ in real-time than a single performance function such as E_c, since not only the adverse effects of the controller on lifetime is considered in J, but also $\mathrm{OpEx_{CS}}$ can be calculated by an unknown function, such as F, with respect to values of degradation $\chi(u)$ (i.e. $\mathrm{OpEx_{CS}} = F(\chi(u))$). However, the current paper is focused on finding possible real-time descriptions of $\chi(u)$ (Section 4) to solve the multi-objective optimisation problem in (7).

Figure 3 shows the required steps needed to be taken to calculate a specific health-sensitive control law from consideration of $\mathrm{LCoE_{CS}}$ (the upper level) and mapping it to a real-time performance function such as J (the lower level) to ranking Pareto-optimal solutions (Emmerich & Deutz 2018), based on certain criteria.

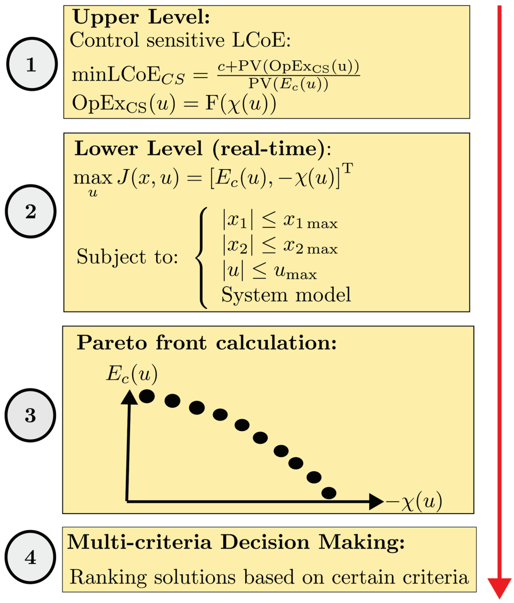

Figure 3. Structure of health-sensitive control problem.

4 STRATEGIES FOR DEGRADATION DESCRIPTION

This section presents possible descriptions for degradation $\chi(u)$ in (7) based on lifetime metrics, such as accumulated fatigue damage, reliability and remaining useful life (RUL).

4.1 *Accumulated fatigue damage*

WECs operating in harsh oceanic environments are exposed to cyclical loading that leads to a physical phenomenon, namely fatigue (Zurkinden et al. 2015, Nielsen et al. 2017). In general, fatigue happens at a microscopic level when a material is under repeated stress, facilitating the growth rate of a tiny crack in the material structure; finally, the crack leads to the failure of a subsystem or even the complete system as time elapses (Shigley et al. 2011). The primary reason for cyclical loading in WECs is the interaction between the control force and existing hydrodynamic forces (i.e. $f_{PTO} - f_{hydro}(z, \dot{z}, \eta)$ in (3)), coupled with the harmonic nature of the wave excitation force.

To evaluate fatigue, the damage due to cyclic loading is accumulated over time. Therefore, to obtain accumulated damage, in the first step, reference S-N curves (S-N defines the number of cycles (N) to failure based on a stress range (S)) (Wöhler 1870) of materials that a component contains, should be obtained. Next, stress-time data (load history) are collected; an algorithm, such as rainflow counting (Muñiz-Calvente et al. 2022) transforms stress-time data into stress-cycle data. Finally, using Miner's rule (Miner 2021), the accumulated fatigue damage (AFD) can be computed (Sanchez et al. 2018) as:

$$\chi(u) = \chi_{AFD}(u) = \sum_{j=1}^{N} \frac{1}{K} s_j^{c_W}, \qquad (8)$$

where c_W and K are material properties, N is number of cycles, and s_j is the stress range in the cycle j. In (Sanchez et al. 2018), $\chi_{AFD}(u)$ has been calculated in real-time using an online rainflow counting algorithm for blade root fatigue of a wind turbine. Therefore, such a real-time fatigue calculation method can potentially be used for health-sensitive control of WECs.

4.2 *Reliability*

Generally, reliability is defined as the ability of a system, subsystem, or component to perform a specific task under certain operational and environmental circumstances within a period (Rausand & Hoyland 2003). This subsection investigates how it is possible to define degradation $\chi(u)$ as a function of deterministic and stochastic reliability. Although the strategy based on redundancy can be categorised as deterministic reliability, it is analysed separately due to its importance.

4.2.1 *Deterministic reliability*

Deterministic reliability is defined as (Rausand & Hoyland 2003):

$$R(t) = e^{-\int_0^t \lambda(t)dt}, \qquad (9)$$

where $\lambda(t)$ is the failure rate (number of failures per unit of time).

Although component failure rate is a function of time (i.e. $\lambda(t)$), a constant failure rate under specific operating conditions is calculated as a nominal failure rate. Therefore, the failure rate of a component does vary with time under various loading conditions. For example, if an actuator in a control system is considered, the failure rate $\lambda(t)$, based on control input (load) u, can be described (Salazar et al. 2017) as:

$$\lambda(t) = \lambda_{nominal}\left(1 + \beta \int_0^t |u(t)|dt\right), \qquad (10)$$

where $\lambda_{nominal}$ is the nominal failure rate of the actuator, and β is a constant. So, the degradation of the actuator can be calculated as:

$$\chi(u(t)) = \chi_R(u(t)) = (1 - R(u(t))). \qquad (11)$$

The big challenge in deterministic reliability is obtaining $\lambda_{nominal}$ for WECs, where failure data is scarce in the wave energy sector (see Section 5).

4.2.2 *Stochastic reliability*

Probabilistic reliability is used when no specific data on the failure rate of a component is available. Hence, reliability is defined as failure probability ($R = P_f$), based on a reliability index (η) of the most probable failure point (Ambühl et al. 2015):

$$P_f = \Phi(-\eta), \qquad (12)$$

where the Φ is the standard normal distribution function.

P_f in (12) can be calculated either by Monte Carlo Simulation (MCS) (Mooney 1997) or by a first-order reliability method (FORM) (Kolios et al. 2018). Nevertheless, the real challenge is that (12) is not based on system variables, such as u. Therefore, the multi-objective problem in (7) cannot be developed. However, in a specific case, if only actuator (PTO) degradation is considered, the degradation can be written as a general stochastic process, dependent on control input and probabilistic reliability. For example, in (Zhang et al. 2022), actuator degradation is regarded as a Winner process (WP):

$$\chi_{WP}(u(t)) = \varphi_0 + \int_0^t \mu_0 \exp(\alpha |u(t)|) \mathrm{d}\tau + \sigma B(t), \qquad (13)$$

where φ_0 is the initial degradation measure; μ_0, σ and α are known parameters specified by a Kalman filter;

and $B(t)$ shows standard Brownian motion ($B(t) \sim N(0, t)$), which represents stochastic degradation dynamic. Therefore, the augmented model of the system, based on probabilistic reliability, can be described, for a general linear time-invariant system, as:

$$\begin{cases} \dot{x}(t) = Ax(t) + B_u R(t) u(t) + B_d d(t), \\ \dot{x}_{n+1}(t) = \mu_0 \exp(\alpha |u(t)|), \\ y(t) = Cx(t) \\ \chi_{wp}(u(t)) = x_{n+1}(t) + \sigma B(t). \\ R(t) = \Phi\left(\frac{\varphi_{\mathrm{U}} - x_{n+1}(t)}{\sigma\sqrt{t}}\right), \end{cases} \tag{14}$$

where $\varphi_{\mathrm{U}} = \varphi - \varphi_0$ is the failure threshold; Φ is the standard normal distribution; A, B_u and B_d are system matrices; and $d(t)$ is a disturbance. Finally, a term such as $\left\| \omega_{\chi,i}(t) \left[\chi_{wp}(t) - r_\chi(t) \right] \right\|_2^2$ can be included in performance function (7), where $r_\chi(t)$ is the reference degradation path, and $\omega_{\chi,i}(t)$ is a time-varying weight based on $R(t)$. A similar stochastic reliability measure can be used for the linearised model of WECs, where $d(t)$ is wave excitation force.

4.2.3 *Redundancy*

A further strategy is based on redundancy and actuator distribution. Redundancy can be considered as a contingency plan when enhancing lifetime through one actuator/sensor is impossible. Consider an LTI control system (Chamseddine et al. 2014) as:

$$\dot{x}(t) = Ax(t) + B_v v^d(t), \tag{15}$$

$$v^d(t) = B_u u(t), \tag{16}$$

where $v^d(t)$ is the desired control effort calculated by a nominal controller. Therefore, control allocation aims to find a u which leads to $v^d(t)$. The control allocation performance function is written (Chamseddine et al. 2014) as:

$$\begin{cases} \min_u u(t)^T W(t) u(t), \\ \text{subject to } B_u u(t) = v^d(t), \end{cases} \tag{17}$$

where $W(t) = \mathrm{diag}([w_1(t) w_2(t) \cdots w_i(t) \cdots w_m(t)])$ is the weight matrix, which specifies the actuator priority level. $W(t)$ is updated based on the global deterministic actuator reliability (e.g. MIT rule-based reliability in Figure 4):

$$\dot{w}_i(t) = \alpha R_g(u(t)) \frac{\partial R_g(u(t))}{\partial w_i}, \quad i = 1, \ldots, m \tag{18}$$

where α is the adaptation rate and $R_g(u)$ is the global deterministic reliability. The control allocation procedure is naturally independent of the nominal controller, depicted in Figure 4. However, the actuator distribution control law (i.e. u) can be augmented with the nominal controller to improve lifetime. For example, for WECs with more than one PTO, such as the Ocean Harvesting Infinity WEC (Technology - Ocean Harvesting), the multi-objective optimisation problem in (7) can be rewritten based on a reference virtual control input $v^d(t)$ instead of $u(t)$. Therefore, the degradation $\chi_{R_g}(v^d(t))$ based on global deterministic reliability $R_g(v^d(t))$, similar to (11), is obtained as:

$$\chi_{R_g}(v^d(t)) = (1 - R_g(v^d(t))). \tag{19}$$

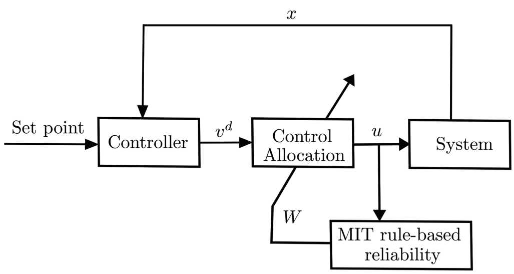

Figure 4. Lifetime enhancement based on control allocation. Adapted from (Chamseddine et al. 2014).

4.3 *Remaining Useful Life (RUL)*

Dissipated energy is reflective of degradation since wear in mechanical systems, such as a friction drive system, accompanies energy dissipation (Obando et al. 2021). For example, dissipated energy for a two-mass flexible drive train of a wind turbine can be modelled (Felix et al. 2023) as:

$$\chi_{E_D}(t) = E_D = \int B_{dt} (\omega_r - \omega_g)^2 dt = \int P_D dt, \tag{20}$$

where ω_r and ω_g are rotor and generator angular velocities, E_D is dissipated energy, P_D is dissipated power, and B_{dt} is the torsion damping coefficient. So, the lifetime-aware control structure can be represented in Figure 5, where λ^* is the wind intensity, which is a reference of the system. So, dissipated energy is controlled by reference modulation as:

$$\lambda^* = \lambda^{opt} + \Delta\lambda, \tag{21}$$

where $\Delta\lambda$ is the output of the RUL controller, generated based on the estimation of degradation $\hat{\chi}_{E_D}(t) = \hat{E}_D(t)$ and a reference RUL (for constructing desired dissipated energy).

For WECs, this idea can be investigated as reference velocity modulation in approximate velocity tracking (AVT) control structure (Ringwood et al. 2023):

$$v_{refn} = v_{ref} + \Delta v, \tag{22}$$

where v_{refn} is the new reference velocity, v_{ref} is the old reference velocity and Δv is the output of a RUL controller. It is worth noting that the reference modulation law in (22) is not in the MOO problem format given in (7).

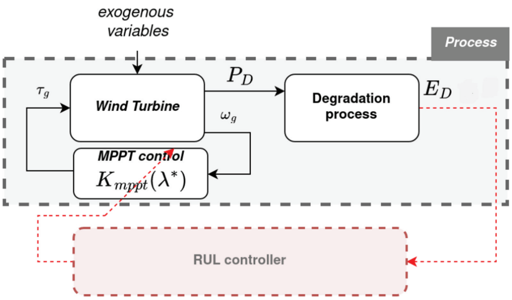

Figure 5. RUL control structure for deteriorating wind turbine with a flexible-shaft drive-train (Felix et al. 2023).

5 DISCUSSION

In this section, all degradation description strategies are evaluated based on implementation requirements and issues to consider when each strategy is used. At the section end, Table 1 summarises the key points discussed in this section and shows the severity of issues and requirements with colour coding.

The primary problem for all strategies described in Section 4 is failure data scarcity in the wave energy sector, while different types of degradation data is required for the different methods. Even though some references like (deCastro et al. 2024) have gathered operational data for various WECs, only a few researchers have tried to specify failure patterns based on operational data. For example, in (M'zoughi et al. 2024), failure patterns of a Wells turbine in an onshore oscillating water column are gathered through operational data. Failure patterns can help estimate nominal failure rates and reference degradation path models of components. However, the study in (M'zoughi et al. 2024) focuses only on a specific type of WEC and PTO subcomponent (i.e. a Wells turbine).

Starting with deterministic reliability in Section 4.2.1, the main requirement is the nominal failure rates $\lambda_{nominal}$ in (10). Considering failure data sparsity, the nominal failure rate is estimated, using failure rates from other industries (Rinaldi et al. 2018), as follows:

$$\hat{\lambda}_{nominal} = \lambda_B \cdot \pi_E \cdot \pi_{FM}, \tag{23}$$

where λ_B is the nominal failure rate of a component in a specific industry, π_E is an environmental factor for considering the operational environment, and π_{FM} is the failure mode factor. After finding $\hat{\lambda}_{nominal}$ for each component, the global failure rate can be achieved based on a reliability block diagram model of the system (see Figure 6). Since all components in Figure 6 are connected in a series structure, the global failure rate of a subsystem, such as PTO, is the addition of failure rates of components inside PTO (Rausand & Hoyland 2003). For example, the global failure rate of the PTO in Figure 6 is the addition of failure rates of the throttle valve, blades, rotor hub, shaft, generator, and back-to-back converter (i.e. AC/DC and DC/AC blocks) . The estimated nominal failure rate $\hat{\lambda}_{nominal}$ in (23) has a large uncertainty compared with the real failure rate $\lambda_{nominal}$. However, the uncertainty can be reduced using accelerated testing and adjusting π_{FM} by obtaining a failure mode and effects analysis (FMEA) table (Weller et al. 2015).

In contrast to deterministic reliability strategies, stochastic reliability (Section 4.2.2) does not need the failure rates of components, but it needs a reference degradation path model $r_\chi(t)$ for the actuator (PTO). The challenge is that it is difficult to consider an accurate degradation path model for a PTO since, at least, we need some failures in the PTO to construct a reference degradation path model. In addition, stochastic reliability cannot give an accurate representation of how each competent inside PTO leads to the failure of PTO itself, since stochastic reliability in Section 4.2.2 does not use a reliability block diagram. Similar to the reference degradation path model in stochastic reliability, the required data for the RUL strategy is a reference RUL. Therefore, a PTO must fail to know how much overall dissipated energy leads to a failure. In addition, the RUL method is the only one that does not have the multi-objective optimisation structure in (7), so it may not lead to a better trade-off between captured energy and OpEx.

Among the strategies presented in Section 4, accumulated fatigue damage has less uncertainty in the requirement phase, since every material has a unique S-N curve, and calculating stress data is straightforward with numerical methods, such as finite element analysis (Bhavikatti 2005). However, accumulated fatigue damage can only be used for specific components inside the PTO, so it is challenging to calculate the damage for the complete PTO. In addition, the accumulated damage needs to be

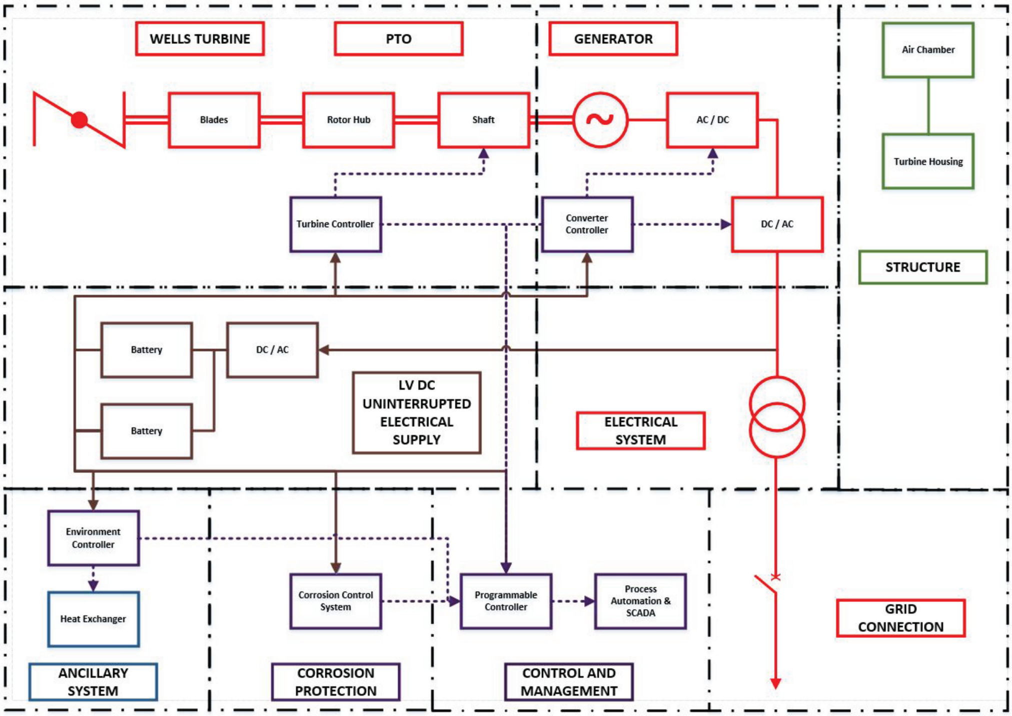

Figure 6. Reliability block diagram for an onshore oscillating water column (Mueller et al. 2016).

Table 1. Evaluation of ideas (i.e. accumulated fatigue damge (AFD), Deterministic reliability (DR), Stochastic reliability (SR), Deterministic reliability-redundancy (DR-Red), and RUL). More severe conditions are shown in red, almost severe in orange, and less severe in green.

Descriptions	Issues (I) and Requirements (R)		
	Less severe	Almost severe	More severe
AFD 4.1	• Load History (R)	•S-N curve of materials (R) • Subsystem analysis (not complete PTO) (I)	• Linearisation of damage (I)
DR 4.2.1		• Failure rates of components (R) • Uncertainty (I)	
SR 4.2.2		• No knowledge about subcomponents (I) (contribution to actuator failure)	• Reference degradation path model (R)
DR-Red 4.2.3		• Failure rates of components (R) •Redundancy (R) • Uncertainty (I)	
RUL 4.3	• Modelling of losses (R)	• Not considering failure modes (I) •Not in (7) format (I)	• Reference RUL (R)

linearised to find its relation with system variables, such as the control input u (Sanchez et al. 2018).

6 CONCLUSIONS

This paper investigates the lifetime-aware control problem for WECs. To develop a lifetime-aware controller, at the first step, a degradation description in real-time should be defined, which correlates control input with degradation. Therefore, it is studied how a degradation model for lifetime-aware control can be obtained based on well-known lifetime metrics, such as reliability, accumulated fatigue damage or remaining useful life (RUL). Each strategy has its pros and cons, but the scarcity of failure data and the existence of many diverse types of WECs are common problems. Among all the strategies, deterministic reliability methods, with the help of the reliability block diagram and an FMEA table, can help to understand better how each subsystem degradation leads to complete system degradation. Nevertheless, the effectiveness of different methods is highly dependent on the unique characteristics and operational conditions of each WEC. Therefore, a suitable degradation evaluation metric should be selected before the lifetime-aware controller design stage to achieve more optimal results.

In future studies, there are some research gaps to investigate. First, it is essential to find a suitable function to calculate OpEx from real-time degradation descriptions. Second, it can be investigated how the failure data sparsity problem in each degradation description is addressed with accelerated testing. Third, it is necessary to focus on solving the proposed multi-objective optimisation problem to reach an acceptable trade-off between captured energy and lifetime enhancement.

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