



Realistic energy-maximising control of cyclorotor wave energy converters using estimator, predictor, and nonlinear MPC

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ABSTRACT

This study presents the first realistic control design for cyclorotor-based Wave Energy Converters (WECs) to maximise energy conversion. The selected approach incorporates a relative foil-fluid velocity estimator and predictor with a nonlinear model predictive controller for a cyclorotor WEC operating in irregular waves. The performance of the proposed realistic controller is compared with that of an idealised case, which assumes perfect knowledge of the relative foil-fluid velocity. Realistic and idealised control are assessed by calculating the annual energy production in two representative ocean regions, and the associated energy losses due to estimation and prediction inaccuracies are quantified. Simulation results indicate that the impact of estimation and prediction errors on energy capture remains within acceptable limits, while realistic estimates of cyclorotor energy output are obtained for the first time.

1. Introduction

Ocean waves represent a vast, yet underutilised, source of renewable energy. Compared to wind and solar, wave energy offers higher power density and generally exhibits greater consistency and predictability (Fusco et al., 2010). Despite several decades of research and development, Wave Energy Converters (WECs) have yet to achieve commercial viability. Although numerous device concepts are proposed and tested, the cost of converting wave energy into electricity remains uncompetitive with other renewable sources, such as wind and solar (Guo and Ringwood, 2021; Guo et al., 2023). Consequently, a key challenge in the field is to reduce the Levelised Cost of Energy (LCoE), either by incorporating advanced control strategies (Ringwood et al., 2023) and/or by designing optimised devices (Ringwood, 2025).

Among the plethora of proposed wave energy devices, cyclorotor WECs (see Fig 1) emerge as a novel and promising technology. Cyclorotor WECs operate by exploiting the interaction between rotating hydrofoils and the orbital motion of water particles in waves. This interaction generates lift forces, whose tangential component produces wave-induced torque on the cyclorotor shaft. A rotational generator converts this torque into electrical power. The unidirectional rotor rotation simplifies energy capture (Ermakov and Ringwood, 2021b), while active control of hydrofoil pitch and rotor speed enables the device to manage structural loads and remain operational in energetic and extreme sea states (Arredondo-Galeana et al., 2024).

However, cyclorotor WECs remain relatively underexplored compared to traditional devices that rely on buoyancy or diffraction forces for power generation. To the best of the authors' knowledge, only one company, the Atargis Energy Corporation (Energy, 2025), is actively developing the CycWEC (Siegel, 2019), an ocean bed mounted cyclorotor WEC concept. In addition, the now completed LiftWEC project (Consortium, 2025a), a three-year initiative funded by Horizon 2020, made a significant contribution to the cyclorotor study and proposes a similar concept of a submerged cyclorotor WEC (Devoy McAuliffe et al., 2024). More recently, a Life Cycle Assessment (LCA) of a wave cyclorotor has been reported, providing the first detailed evaluation of the environmental performance of cyclorotor-based WECs (Bastos et al., 2025). Other, potentially less developed, but noteworthy, concepts include the pioneering single rotating hydrofoil investigated in (Hermans et al., 1990; Pinkster and Hermans, 2007), as well as the four-hydrofoil cyclorotor configurations proposed in (Scharmann, 2018) (ocean-bed-mounted) and (Yu et al., 2021) (pontoon-mounted).

As a wave-terminator device, the cyclorotor WEC can absorb up to 70% of incoming wave energy, or even cancel it entirely (Siegel, 2014, 2015), offering potential additional benefits for coastal protection and offshore wind farm shielding (Cui et al., 2024). According to the simulations presented in (Arguilé-Pérez et al., 2022), the cyclorotor WEC achieves the highest performance on the Galician coast (north-west Spain), with an electrical energy output of about 40% and a capacity factor of approximately 45%, outperforming more traditional WECs.

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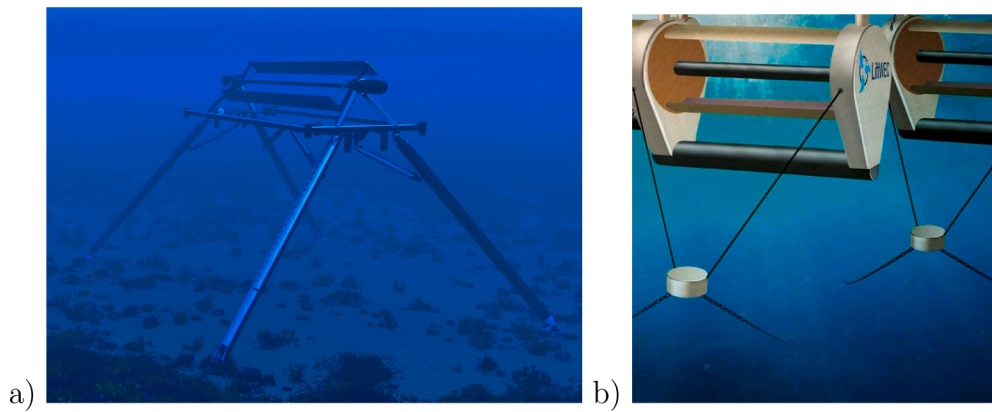


Fig. 1. Concepts of a) CycWEC (Energy, 2025) and b) LiftWEC (Consortium, 2025a,b), cyclorotor WECs.

Performance assessments estimate a mean annual power production of 619 kW for the CycWEC concept deployed at the Humboldt Bay off the US West Coast (Siegel, 2019), and 294.5 kW for the LiftWEC concept off the North Atlantic coast of France (Devoy McAuliffe et al., 2024), noting that the LiftWEC hydrofoil span is half that of the CycWEC rotor. Corresponding LCoE estimates are approximately 105 USD/MWh (96 EUR/MWh) for CycWEC (Energy, 2025), and 126–190 EUR/MWh for LiftWEC (Devoy McAuliffe et al., 2024), which compares favourably with floating offshore wind (Martinez and Iglesias, 2024). Both studies highlight *optimised cyclorotor WEC control* as a key strategy for further reducing LCoE.

Unfortunately, despite these promising results, cyclorotor WECs have not gained widespread attention. The main challenges in cyclorotor WEC development are the high nonlinearity of the mathematical models and the complexity of experimental testing (Siegel, 2019; Ermakov et al., 2023b; Lamont-Kane et al., 2024; Olbert and Abdel-Maksoud, 2023). Although the first concept of a cyclorotor WEC was introduced more than 30 years ago (Hermans et al., 1990), a realistic control architecture that incorporates both an estimator and predictor of the rapidly changing wave-induced fluid velocity field, along with a control algorithm for accurate performance and loss assessment, remains lacking. Early studies often evaluated performance in terms of wave power cancellation (Siegel, 2019, 2014; Siegel et al., 2011, 2012), measured by the difference between the energy of incident and transmitted waves. In this approach, the control strategy (Siegel, 2019, 2014) identifies the fundamental wave in the incoming irregular spectrum and adjusts the cyclorotor pitch, phase, and rotational speed to generate an opposite-phase wave that cancels the incoming one. Later research demonstrated that targeting wave cancellation alone does not accurately represent device efficiency (Ermakov et al., 2023b, 2022b). As a result, several studies now focus on rotor shaft mechanical power output as the performance metric (Arredondo-Galeana et al., 2024; Ermakov et al., 2022a), applying a pseudo-spectral control method to determine optimal pitch and velocity actuation. However, this method requires substantial computation time. Most numerical performance evaluations are carried out in (relatively unrealistic) regular wave conditions (Siegel, 2019; Ermakov et al., 2023b) or in short-duration simulations of irregular waves, typically lasting less than 15 minutes (Arredondo-Galeana et al., 2024; Ermakov et al., 2022a; Ringwood and Ermakov, 2022), which may not yield statistically significant results. Some tested control strategies, such as those in (Arredondo-Galeana et al., 2024; Ermakov et al., 2022a; Stasinopoulos et al., 2025a,b), also assume perfect knowledge of the fluid velocity relative to the hydrofoils, and therefore do not account for potential losses from estimation and prediction errors.

This article introduces the first realistic energy-maximising control system for a cyclorotor WEC, integrating an estimator and a predictor of the relative foil-fluid velocity in irregular waves, together with a Nonlinear Model Predictive Control (NMPC) approach. Cyclorotor WEC control

presents unique challenges due to its lift-force-driven operating principle, the diverse set of sensors involved, and the strong nonlinearity of the mathematical model. The inclusion of an estimator and a predictor allows for a more realistic representation of practical operation, where current and future values of the relative foil-fluid velocity need to be reconstructed from noisy measurements from a sensor system. The sensor system consists of foil-mounted force sensors, main shaft sensors for angular velocity, and an up-wave gauge for free surface elevation. The severe nonlinearity of cyclorotor WEC mathematical models, combined with the rapidly changing relative foil-fluid velocity that serves as the system input, makes this estimator-predictor-NMPC structure fundamentally different from existing control formulations for traditional WECs.

The performance of the developed realistic controller is compared against the idealised case, where perfect knowledge of the relative foil-fluid velocity is assumed. The performance function is explicitly formulated to mainly maximise the extracted mechanical energy, under specified system constraints. The reduction in energy capture due to the inaccuracies in estimation and prediction is quantified, and found to be within acceptable limits. For the first time, realistic estimates of annual mechanical energy production of a cyclorotor WEC in two representative ocean regions are obtained.

The remainder of the paper is structured as follows: Section 2 describes the mathematical models for irregular ocean waves and the hydrodynamics of cyclorotor WEC rotation in waves. Section 3 introduces the performance metrics used for control algorithm evaluation and annual energy production assessment. Section 4 details the developed control architecture, which includes an estimator, a predictor of the relative foil-fluid velocity, and a NMPC scheme adapted for the cyclorotor WEC. Section 5 evaluates the accuracy of the proposed estimator and predictor, as well as the performance of the developed realistic control system. Annual energy output results are presented for two ocean sites with distinct wave climates, for both realistic and idealised control, and the energy capture losses due to estimation and prediction inaccuracies are quantified. Finally, Section 6 discusses the key technological advantages identified in this study and evaluates the future potential and feasibility of cyclorotor WECs, based on the findings.

2. Control-oriented mathematical models for cyclorotor WEC

2.1. Representation of irregular wave environments

Following the approach in (Arredondo-Galeana et al., 2024), the cyclorotor WEC is assumed to operate in irregular waves modeled using the Joint North Sea Wave Project (JONSWAP) spectrum (Veritas, 2010), which provides a realistic representation of the broad frequency content (panchromatic nature) of ocean waves. The JONSWAP spectrum is a modification of the Pierson-Moskowitz spectrum, incorporating a

peak enhancement factor to reflect more sharply peaked spectral energy distributions. The spectrum is discretized in the frequency domain (Jeans et al., 2013; Jalón and Brennan, 2020; Mérigaud and Ringwood, 2018) and represented as a superposition of n individual regular (monochromatic) wave components indexed by j , whose amplitudes A_j are computed as:

$$A_j = \sqrt{2S_A(\omega_j)\Delta\omega}, \quad (1)$$

where $S_A(\omega_j)$ is the spectral density at frequency ω_j , with $\Delta\omega$ denoting the frequency discretization step.

The Pierson-Moskowitz spectrum, S_{PM} , is defined as:

$$S_{PM}(\omega_j) = \frac{5}{16} H_s^2 \omega_p^4 \omega_j^{-5} \exp \left[-\frac{5}{4} \left(\frac{\omega_j}{\omega_p} \right)^{-4} \right], \quad (2)$$

where H_s is the significant wave height, and $\omega_p = 2\pi/T_p$ is the peak wave frequency corresponding to the peak wave period T_p .

The spectral density function of the JONSWAP spectrum is then given by:

$$S_J(\omega_j) = A_{\tilde{\gamma}} S_{PM}(\omega_j) \tilde{\gamma}^{\exp \left[-\frac{1}{2} \left(\frac{\omega_j - \omega_p}{\sigma \omega_p} \right)^2 \right]}, \quad (3)$$

where $A_{\tilde{\gamma}} = 1 - 0.287 \ln(\tilde{\gamma})$ is a scaling coefficient, and $\tilde{\gamma} = 3.3$ is the peak enhancement factor. The spectral width parameter σ is defined piecewise as:

$$\sigma = \begin{cases} 0.07, & \text{if } \omega_j \leq \omega_p, \\ 0.09, & \text{if } \omega_j > \omega_p. \end{cases} \quad (4)$$

In this study, the total annual energy production is evaluated for two sea locations, one in Humboldt Bay (see Fig. 3) with a water depth of 117 m, and one in the Bay of Biscay (see Fig. 4) with a water depth of 66.5 m. For these water depths, assuming an infinite depth results in approximately 1% relative error in the average wave-induced fluid velocity, under a moderate irregular sea state (peak period $T_p = 10$ s, significant wave height $H_s = 2$ m). For a more energetic sea state (peak period $T_p = 14$ s, significant wave height $H_s = 4$ m), the corresponding relative error is about 4%. The errors are obtained by direct numerical comparison between linear finite-depth and deep-water wave kinematics, evaluated over the submergence depth range relevant to cyclorotor WEC operation. Therefore, assuming linear deep-water wave theory (Airy, 1845) introduces a very small modelling inaccuracy, while significantly improving the computational time. Consequently, the wave-induced fluid velocity field components $\mathbf{V}_W = \{(V_W)_x, (V_W)_y\}$ at an underwater location with coordinates (x, y) can be computed as:

$$(V_W)_x = \sum_{j=1}^n \frac{\pi A_j}{T_j} e^{k_j y} \cos(k_j x - \omega_j t + \phi_j), \quad (5)$$

$$(V_W)_y = \sum_{j=1}^n \frac{\pi A_j}{T_j} e^{k_j y} \sin(k_j x - \omega_j t + \phi_j),$$

where $g = 9.81 \text{ m/s}^2$ is gravitational acceleration, $T_j = 2\pi/\omega_j$ is the period of the j -th wave component, $k_j = \omega_j^2/g$ is the corresponding wave number (from the linear deep-water dispersion relation) (McCormick, 2013), and ϕ_j is a random phase uniformly distributed in $[0, 2\pi]$.

The wave power per unit crest length, $P_{W\text{ave}}$, available for extraction by the WEC in an irregular wave field is estimated as:

$$P_{W\text{ave}} = \frac{1}{64\pi} \rho g^2 H_s^2 T_e, \quad (6)$$

where $\rho = 1000 \text{ kg/m}^3$ is the water density, and $T_e = 0.8 T_p$ is the energy period of the sea state, following (McCormick, 2013; Arredondo-Galeana et al., 2024).

2.2. Dynamic model of the cyclorotor-based wave energy converter

The rotational dynamics of a cyclorotor WEC, operating in irregular waves, are described by a two-dimensional, control-oriented mathematical model, initially proposed in (Ermakov and Ringwood, 2021a,d)

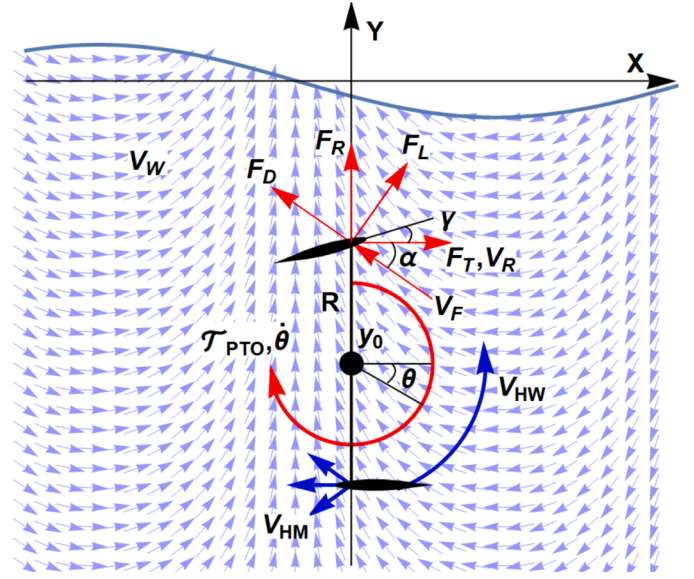


Fig. 2. Two-dimensional mathematical model illustrating the operating principle of a cyclorotor WEC.

and later validated against various numerical models and experimental results in (Ermakov et al., 2023b; Ermakov and Ringwood, 2021c; Arredondo-Galeana et al., 2023a; Ermakov and Ringwood, 2022). A schematic, illustrating the interaction between a twin-foil cyclorotor WEC, the incident wave field, and the rotation-induced fluid velocity, is presented in Fig. 2.

For a twin-foil cyclorotor with radius R , submerged at a depth y_0 , the Cartesian coordinates of the hydrofoil positions are given by:

$$\begin{aligned} x_i(t) &= R \cos[\theta(t) + \pi(i-1)], \\ y_i(t) &= y_0 - R \sin[\theta(t) + \pi(i-1)], \end{aligned} \quad (7)$$

where $i = 1, 2$ denotes the hydrofoil index, $\theta(t)$ is the cyclorotor angular position in polar coordinates, and the phase shift $\pi(i-1)$ ensures that the two hydrofoils remain positioned diametrically opposite each other.

The rotational velocity vector $\mathbf{V}_{R_i}$ of hydrofoil i , is obtained by differentiating the hydrofoil position in (7) with respect to time, yielding the following Cartesian components:

$$\begin{aligned} (V_{R_i})_x &= -R \dot{\theta} \sin[\theta(t) + \pi(i-1)], \\ (V_{R_i})_y &= -R \dot{\theta} \cos[\theta(t) + \pi(i-1)], \end{aligned} \quad (8)$$

where $\dot{\theta}$ denotes the angular velocity of the cyclorotor.

As the cyclorotor rotates within the wave-induced fluid velocity field, the hydrofoils are subject to lift F_L and drag F_D forces. For a given hydrofoil i , these forces depend on the relative foil-fluid velocity vector $\mathbf{V}_{F_i}$, defined as the vector difference between the local wave-induced fluid velocity $\mathbf{V}_{W_i}$ and the hydrofoil rotational velocity $\mathbf{V}_{R_i}$, with an additional contribution from wake-induced and radiative effects represented by $\mathbf{V}_{H_i}$:

$$\mathbf{V}_{F_i} = \mathbf{V}_{W_i} - \mathbf{V}_{R_i} + \mathbf{V}_{H_i}. \quad (9)$$

This formulation allows the effects of the trailing wake, generated by the rotating hydrofoils, to be articulated.

The instantaneous radiation and trailing wakes, generated by the rotating hydrofoils, are described using a complex potential formulation, initially introduced in (Wehausen and Laitone, 1960), adapted for hydrofoil modeling in (Hermans et al., 1990), and later simplified via an analytical solution in (Ermakov et al., 2023b):

$$F(z, t) = \frac{\Gamma(t)}{2\pi j} \log \left[\frac{z - c(t)}{z - \bar{c}(t)} \right] -$$

$$\frac{2j\sqrt{g}}{\pi} \int_0^t \frac{\Gamma(\tau)}{\sqrt{j(z - \tilde{c}(\tau))}} D_w \left[\frac{\sqrt{g}(t - \tau)}{2\sqrt{j(z - \tilde{c}(\tau))}} \right] d\tau, \quad (10)$$

where $z = x + jy$ denotes the complex spatial coordinate, $c(\tau) = x(\tau) + jy(\tau)$ is the complex position of the point vortex in the z -plane at an earlier time τ , $\tilde{c}(\tau)$ is the position of the mirror point vortex, Γ is the circulation strength of the point vortex, and $D_w(x)$ is the Dawson function (Dawson, 1897), defined as:

$$D_w(x) = e^{-x^2} \int_0^x e^{y^2} dy. \quad (11)$$

The velocity field of the radiated waves generated by the hydrofoil motion is then given by the complex derivative of the potential with respect to z :

$$\mathbf{V}_H = \frac{\partial F(z, t)}{\partial z} = (\mathbf{V}_H)_x - j(\mathbf{V}_H)_y \quad (12)$$

It should be noted that the first term in Eq. (10) represents the instantaneous radiation from the moving hydrofoil, denoted by $\mathbf{V}_{HM}$, while the second (integral) term captures the trailing wake left by the hydrofoil, denoted by $\mathbf{V}_{HW}$. Accordingly, for hydrofoil i , the total foil-induced fluid velocity vector $\mathbf{V}_{H_i}$ is calculated as the sum of the self-induced wake velocity $\mathbf{V}_{HW_i}$, the wake velocity from the opposing hydrofoil $\mathbf{V}_{HW_j}$, and the instantaneous radiation velocity generated by the motion of the opposite foil $\mathbf{V}_{HM_j}$:

$$\mathbf{V}_{H_i} = \mathbf{V}_{HM_j} + \mathbf{V}_{HW_i} + \mathbf{V}_{HW_j}. \quad (13)$$

Once all the components of the relative foil-fluid velocity vector $\mathbf{V}_{F_i}$ are defined, the angle of attack for hydrofoil i can be calculated as:

$$\alpha_i(t) = \arcsin \left[\frac{(V_{R_i})_x * (V_{F_i})_y - (V_{R_i})_y * (V_{F_i})_x}{|V_{R_i}| |V_{F_i}|} \right] + \gamma_i, \quad (14)$$

where γ_i is the pitch angle of hydrofoil i .

The lift F_L and drag F_D forces acting on the hydrofoils, resulting from their interaction with the relative foil-fluid velocity $\mathbf{V}_{F_i}$, can be computed as:

$$F_{L_i} = \frac{1}{2} \rho C C_L(\alpha_i) |V_{F_i}|^2, \quad F_{D_i} = \frac{1}{2} \rho C C_D(\alpha_i) |V_{F_i}|^2, \quad (15)$$

where C is the chord length of the hydrofoil, ρ is the fluid density, and C_L and C_D are the lift and drag coefficients, respectively. These coefficients are obtained as functions of the angle of attack α_i , based on experimental data for NACA0015 hydrofoils reported in (Sheldahl and Klimas, 1981), following the approach described in (Siegel, 2019).

Then, the intensity of circulation of the vortex $\Gamma(t)$ can be determined from the Kutta-Joukowski theorem (Batchelor, 1967), as it is proportional to the lift force F_L generated on the hydrofoil:

$$\Gamma = F_L / (\rho |V_F|) = \frac{1}{2} C_L(\alpha) |V_F| C. \quad (16)$$

The tangential F_T and radial F_R components of the hydrodynamic loadings on each hydrofoil are determined by projecting the lift and drag forces onto the local tangential and radial directions of the hydrofoil trajectory:

$$\begin{aligned} F_{T_i} &= F_{L_i} \sin(\alpha_i - \gamma_i) - F_{D_i} \cos(\alpha_i - \gamma_i), \\ F_{R_i} &= F_{L_i} \cos(\alpha_i - \gamma_i) + F_{D_i} \sin(\alpha_i - \gamma_i). \end{aligned} \quad (17)$$

The tangential force F_T contributes directly to wave energy extraction, while the radial force F_R induces structural loads that must be minimized to avoid fatigue and damage to a cyclorotor structure (Arredondo-Galeana et al., 2024). Consequently, the total wave-induced torque on the cyclorotor shaft, $\mathcal{T}_{Wave}$, can be found as:

$$\mathcal{T}_{Wave} = (F_{T_1} + F_{T_2})R. \quad (18)$$

Wave energy can be extracted by applying a counteracting torque, $\mathcal{T}_{PTO}$, through a Power Take-Off (PTO) system (typically an electrical generator) installed on the main shaft of the cyclorotor WEC (see Fig. 2).

The resulting rotational dynamics of the cyclorotor are governed by Newton's second law for rotational motion:

$$\ddot{\theta}(t) = \frac{\mathcal{T}_{Wave} - \mathcal{T}_{PTO}}{I}, \quad (19)$$

where $\ddot{\theta}(t)$ is the angular acceleration, and I is the cyclorotor moment of inertia, estimated as $I = 2mR^2$, with m representing the mass of each hydrofoil cross section.

3. Performance metric

The primary performance optimization objective of this study is the maximization of mechanical energy conversion. This performance metric allows clear assessment of energy losses due to hydrodynamic drag and provides a direct evaluation of the torque on the cyclorotor shaft (Ermakov et al., 2023b, 2022b). Accordingly, the time-averaged mechanical shaft power generated by the cyclorotor WEC is defined as the time integral of the product of the rotational velocity $\dot{\theta}$ and the applied PTO torque $\mathcal{T}_{PTO}$, over the time interval $[0, T_0]$:

$$\bar{P}_{Shaft} = \frac{1}{T_0} \int_0^{T_0} \mathcal{T}_{PTO} \dot{\theta}(t) dt. \quad (20)$$

The maximization of mechanical energy conversion from the cyclorotor WEC must be balanced against the minimization of structural loading and fluctuations in the central shaft torque, as proposed in (Stasinopoulos et al., 2025a,b). These fluctuations induce significant cyclical structural loads, due to frequent variations in radial forces F_R . As shown in (Arredondo-Galeana et al., 2024), such cyclical loading contributes to fatigue in the cyclorotor structure, ultimately reducing the device operational lifespan, increasing the frequency of required maintenance, and consequently increasing the LCoE. Therefore, the following performance function is adopted as a key metric for performance assessment in this research:

$$J = \frac{1}{T_0} \int_0^{T_0} (\mathcal{T}_{PTO} \dot{\theta} - \mu \Delta \mathcal{T}_{PTO}^2) dt, \quad (21)$$

where μ is a tunable weighting factor that penalizes large fluctuations in PTO torque, and $\Delta \mathcal{T}_{PTO}$ denotes the maximum variation in PTO torque observed over the time interval T_0 . Formulation (21) of the performance function also results in a convex optimization problem, which facilitates the application of advanced control strategies.

An additional metric used in this study to evaluate the efficiency of wave energy conversion is the Capture Width Ratio (CWR) (Babarit, 2015). It is defined as the ratio of the generated mechanical power $\bar{P}_{Shaft}$ to the available wave power P_{Wave} (as given by Eq. (6)) per 1 m of cyclorotor span, expressed as a percentage:

$$CWR = \frac{\bar{P}_{Shaft}}{P_{Wave}} \times 100\%. \quad (22)$$

Potential annual mechanical energy generation is estimated using sea-state scatter plots that represent the joint probability distribution $p(H_s, T_p)$ of significant wave height H_s and peak wave period T_p for two representative sea regions. The first sea region is the US West Coast at Humboldt Bay (40.53° N, 124.21° W), originally proposed for the CycWEC concept (Siegel, 2019). The second ocean region is located along the North Atlantic coast of France, near the Bay of Biscay (47.84° N, 4.83° W), which was originally proposed to assess the performance of the LiftWEC concept (Ermakov et al., 2022a; Arredondo-Galeana et al., 2024; Devoy McAuliffe et al., 2024). The scatter plots in Fig. 3 and Fig. 4 show the ocean wave conditions at Humboldt Bay and the Bay of Biscay, accordingly. The data presented in the figures are obtained from the ERA5 dataset (ECMWF, 2025) and reflect the most recent annual statistics available for the year 2024. ERA5, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), is the institution's fifth-generation atmospheric reanalysis dataset.

Thus, the total annual mechanical energy production, denoted as E_{Annual} , is calculated using the following expression. It sums the product

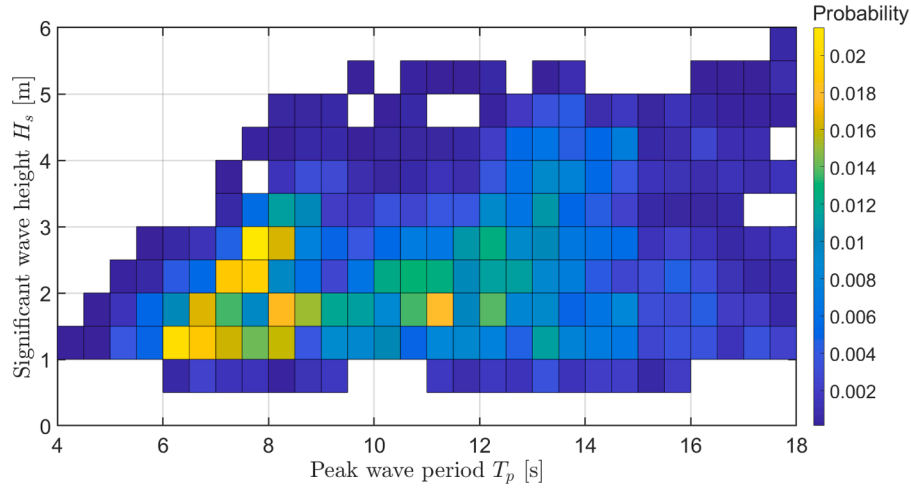


Fig. 3. Scatter plot of the probability distribution of sea state occurrence at Humboldt Bay, off the coast of California, USA, for the year 2024.

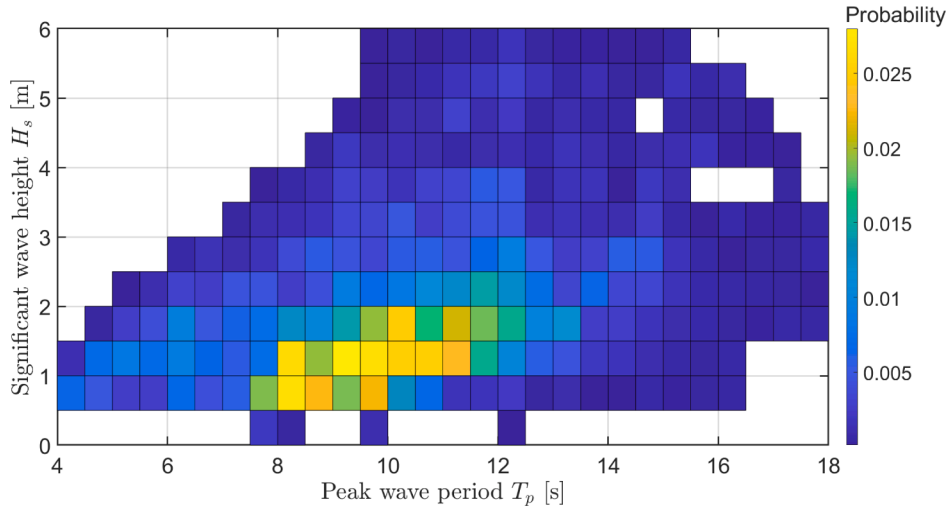


Fig. 4. Scatter plot of the probability distribution of sea state occurrence along the North Atlantic coast of France, near the Bay of Biscay, for the year 2024.

of the time-averaged power output for each sea state, $\bar{P}_{Shaft}(H_s, T_p)$, its probability of occurrence, $p(H_s, T_p)$, and the total number of seconds in a year, $T_{Seconds} = 31,536,000$ s:

$$E_{Annual} = \sum_{T_p} \sum_{H_s} \bar{P}_{Shaft}(H_s, T_p) \cdot p(H_s, T_p) \cdot T_{Seconds}. \quad (23)$$

4. Realistic control system for a cyclorotor WEC

4.1. Control architecture

The proposed realistic control architecture for a cyclorotor WEC is illustrated in Fig. 5. Wind-induced perturbations of the free water surface η generate waves and induce the circulation of water particles, V_{W1} and V_{W2} . The interaction between the rotating hydrofoils and these circulating water particles produces tangential forces F_{T1} and F_{T2} , which drive cyclorotor rotation, as well as radial forces F_{R1} and F_{R2} . The rotational motion of the cyclorotor shaft is described by the angular position θ and angular velocity $\dot{\theta}$, both measured in real time by the sensor system, as demonstrated experimentally in (Ermakov et al., 2023b). Sensors also measure the instantaneous tangential and radial forces. All sensor measurements are denoted with a tilde (e.g., $\tilde{F}_{T1}$, $\tilde{\theta}$) to distinguish them from the true values.

The instantaneous wave-induced fluid velocity V_W , which cannot be directly measured, is estimated using an Extended Kalman Filter

(EKF). The relative foil-fluid velocity V_F is then reconstructed, according to Eq. (9), using direct measurements of the rotational velocity V_R and calculating the contributions of radiation and wake effects V_H deterministically. In addition to providing these estimates, the EKF attenuates measurement noise, improving data reliability. The estimated instantaneous wave-induced fluid velocities for both hydrofoils, V_{W1}^{Est} and V_{W2}^{Est} , together with free-surface elevation measurements $\tilde{\eta}$ from an up-wave gauge, are used as inputs to a Long Short-Term Memory (LSTM) predictor. This predictor plays a key role in the NMPC strategy, generating forecasts of the wave-induced fluid velocity, V_{W1}^{Pred} and V_{W2}^{Pred} , within the prediction horizon.

The estimated and predicted velocity values are then employed by the NMPC framework to compute optimal control actions over the prediction horizon. Specifically, the NMPC determines reference values for the PTO torque, $\mathcal{T}_{Ref}$, and the hydrofoil pitch angles, γ_1^{Ref} and γ_2^{Ref} , with the objective described by the performance function in Eq. (21), while satisfying system constraints. These reference commands are implemented by the PTO and pitch actuation subsystems. The resulting mechanical shaft power, $\bar{P}_{Shaft}$, serves as the primary metric for assessing system performance.

The integration of the estimator, predictor, and NMPC forms a realistic closed-loop control architecture capable of real-time operation across a range of sea states and wave climates. The detailed formula-

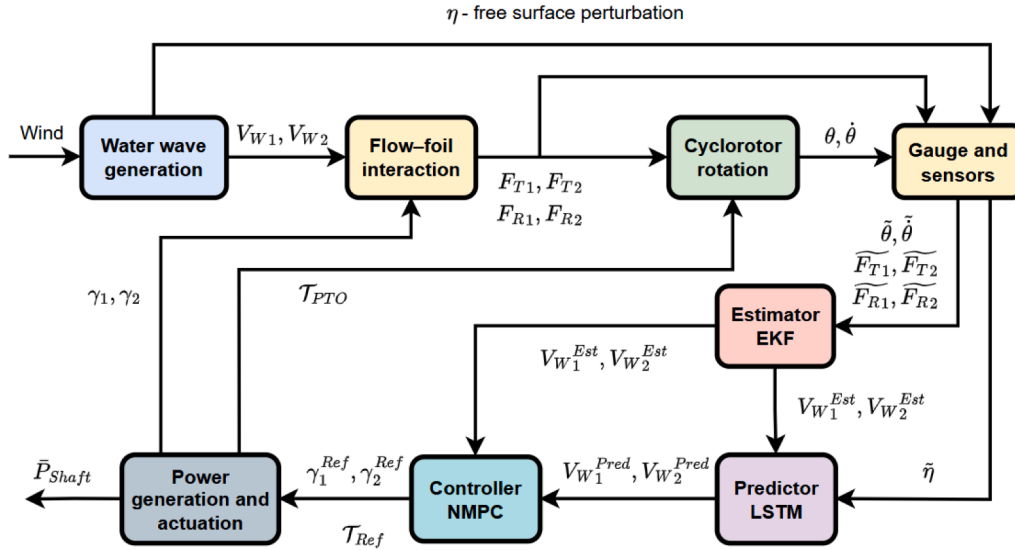


Fig. 5. Diagram of the proposed realistic control architecture for a cyclorotor WEC.

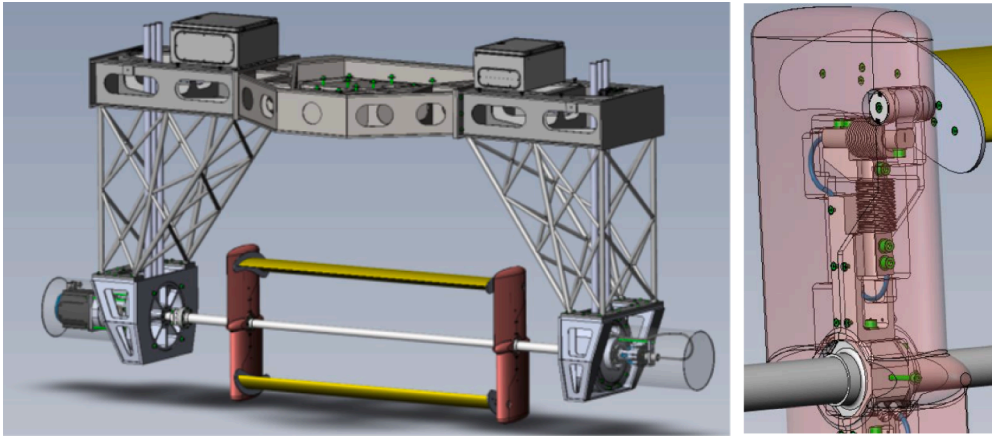


Fig. 6. (a) Experimental scaled prototype of the LiftWEC with two hydrofoils (Ermakov et al., 2023c), (b) Struts, end-plates, and sensors for measuring tangential and radial forces, angular velocity, and hydrofoil positions mounted on the cyclorotor arms.

tions of the estimator, predictor, and control algorithms are presented in subsections 4.2, 4.3 and 4.4, respectively.

4.2. Estimator for relative foil-fluid velocity

The first step in the realistic control design of a cyclorotor WEC is the accurate estimation of the system state, which is essential for determining the control actions required to maximize wave power extraction. Experiments conducted by Atargis (Siegel, 2015; Siegel et al., 2012) and within the LiftWEC project (Ermakov et al., 2023b,a,c) demonstrate that cyclorotor hydrofoils can be equipped with sensors (see Fig. 6) to measure tangential forces F_T and radial forces F_R , while sensors installed on the main shaft can measure hydrofoil angular position θ , angular velocity $\dot{\theta}$, and the resulting wave-induced torque τ_{Wave} . However, as with most measurement systems, sensor data is inevitably affected by noise, which must be filtered to provide a reliable input for control algorithms.

Similar to traditional point-absorber-type WECs, where the implementation of an effective control strategy requires knowledge of the wave-induced excitation force (which cannot be measured directly and therefore, must be estimated (Peña-Sanchez et al., 2020)), the effective control of a cyclorotor WEC relies on accurate knowledge of the instantaneous relative foil-fluid velocity $\mathbf{V}_F$ for each hydrofoil. Knowledge of $\mathbf{V}_F$

enables the system to maintain an optimal angle of attack by adjusting the hydrofoil pitch angles γ_1, γ_2 , and/or the cyclorotor angular velocity, through modulation of the PTO torque τ_{PTO} . From this perspective, the operating principle of a cyclorotor WEC somewhat resembles that of wind and tidal turbines. However, unlike those systems, the relative foil-fluid velocity $\mathbf{V}_F$ in a cyclorotor WEC varies much more rapidly due to the spatial and temporal non-uniformity of the wave-induced fluid velocity field. As a result, the two hydrofoils often experience significantly different values of $\mathbf{V}_F$, and corresponding angles of attack, at any given moment (see Figs. 2 and 8). Therefore, accurate and high-frequency estimation of the relative foil-fluid velocity $\mathbf{V}_F$, for each hydrofoil, is crucial for successful control.

While the primary objective of the estimator for the cyclorotor WEC is to estimate the relative foil-fluid velocity $\mathbf{V}_F$, directly estimating the contribution of the wake-induced fluid velocity components $\mathbf{V}_H$ is computationally intensive and unsuitable for real-time implementation. Moreover, numerical tests show that including $\mathbf{V}_H$ can increase estimation errors. Therefore, the developed EKF focuses solely on estimating the wave-induced fluid velocity components $\mathbf{V}_W$, while the contributions from radiation and wake effects are computed deterministically using Eq. (13). Then, since the components of the rotational velocity $\mathbf{V}_R$ are directly measurable, the relative foil-fluid velocity $\mathbf{V}_F$ components can be reconstructed via Eq. (9). Additional EKF parameters include

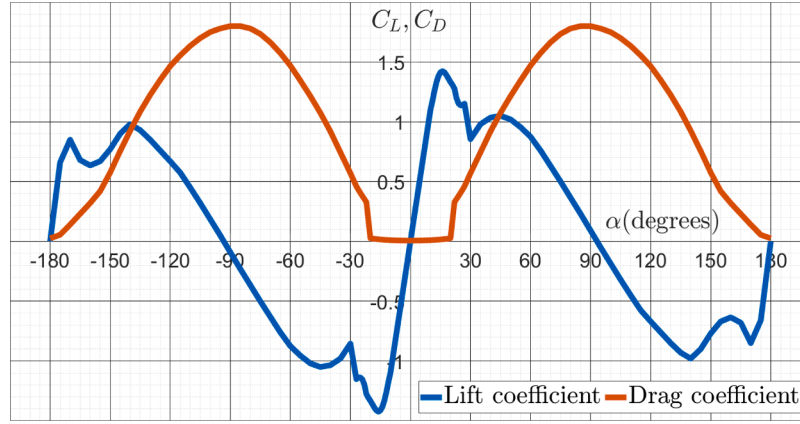


Fig. 7. Lift C_L and drag C_D coefficients for a NACA0015 hydrofoil as functions of the angle of attack α at Reynolds number $Re = 10^7$.

structural properties of the cyclorotor WEC, such as rotor radius R and moment of inertia I , as well as fast control inputs, including hydrofoil pitch angles γ_1, γ_2 , and PTO torque $\mathcal{T}_{PTO}$.

Due to the strong nonlinearity of the mathematical model for the cyclorotor WEC, as detailed in Section 2, a nonlinear state observer, based on the EKF, is employed for noise reduction and estimation of the relative foil-fluid velocity $\mathbf{V}_F$, as also proposed in (Stasinopoulos et al., 2025c). According to the two-dimensional mathematical model (19), the state function $\mathcal{M}$ of the cyclorotor WEC is governed by Newton's second law of rotational motion, expressed as:

$$\ddot{\theta} = \frac{(F_{T_1}(\gamma_1, \dot{\theta}, V_{W_1}) + F_{T_2}(\gamma_2, \dot{\theta}, V_{W_2}))R - \mathcal{T}_{PTO}}{I}, \quad (24)$$

or

$$\ddot{\theta} = \mathcal{M}[\dot{\theta}, (V_{W_1})_x, (V_{W_1})_y, (V_{W_2})_x, (V_{W_2})_y]. \quad (25)$$

The mathematical models for the state function (25) and the sensor measurements, along with the experimentally obtained lift and drag coefficient curves shown in Fig. 7, are highly nonlinear. As a result, there are significant nonlinear relationships between the measurable forces and the wave-induced foil-fluid velocity. Therefore, the EKF is essential to apply the Jacobian matrix to linearize both the system dynamics and the measurement functions around the current state estimate.

Then, the state transition and measurement functions for the EKF are defined as:

$$\mathbf{f} = \{\mathcal{M}, (V_{W_1})_x, (V_{W_1})_y, (V_{W_2})_x, (V_{W_2})_y\}^T, \quad (26)$$

$$\mathbf{h} = \{\tilde{\theta}, \tilde{F}_{T_1}, \tilde{F}_{R_1}, \tilde{F}_{T_2}, \tilde{F}_{R_2}\}, \quad (27)$$

respectively, where all sensor measurements are denoted by tilde.

Within the EKF framework, the state vector of the cyclorotor WEC system is defined as:

$$\xi = \{\dot{\theta}, (V_{W_1})_x, (V_{W_1})_y, (V_{W_2})_x, (V_{W_2})_y\},$$

while the control input vector is given by:

$$\mathbf{u} = \{\gamma_1, \gamma_2, \mathcal{T}_{PTO}\}.$$

The complete list of estimator parameters, including measurable and estimated values, as well as constants, variables, and control inputs, is presented in Table 1.

The state transition function $\mathbf{f}$ and the measurement function $\mathbf{h}$ are expressed as:

$$\dot{\xi}(t) = \mathbf{f}[\xi(t), \mathbf{u}(t)] + \mathbf{w}(t), \quad (28)$$

$$\zeta(t) = \mathbf{h}[\xi(t), \mathbf{u}(t)] + \mathbf{v}(t), \quad (29)$$

Table 1
Estimator parameters.

Measurable variables:	$\tilde{\theta}, \tilde{F}_{T_1}, \tilde{F}_{R_1}, \tilde{F}_{T_2}, \tilde{F}_{R_2}$
Estimated variables:	$\dot{\theta}^{Est}, (V_{W_1}^{Est})_x, (V_{W_1}^{Est})_y, (V_{W_2}^{Est})_x, (V_{W_2}^{Est})_y$
Constants:	R, I
Other variables:	$\dot{\theta}$
Control inputs:	$\gamma_1, \gamma_2, \mathcal{T}_{PTO}$

where $\mathbf{w}(t)$ and $\mathbf{v}(t)$ are zero-mean Gaussian noise vectors representing model and measurement uncertainty, with covariance matrices $\mathbf{Q}_\xi(t)$ and $\mathbf{Q}_\zeta(t)$, respectively: $\mathbf{w}(t) \sim N[0, \mathbf{Q}_\xi(t)]$, $\mathbf{v}(t) \sim N[0, \mathbf{Q}_\zeta(t)]$.

Linearization around the current state estimate is performed using the Jacobians:

$$\mathbf{F}(t) = \left. \frac{\partial \mathbf{f}}{\partial \xi} \right|_{\xi(t), \mathbf{u}(t)}, \quad \mathbf{H}(t) = \left. \frac{\partial \mathbf{h}}{\partial \xi} \right|_{\xi(t), \mathbf{u}(t)}, \quad (30)$$

where $\mathbf{F}$ is the state-transition model, $\mathbf{H}$ is the observation model.

The EKF operates in two phases, prediction and update, which are governed by the following equations:

$$\dot{\xi}^{Est}(t) = \mathbf{f}[\xi^{Est}(t), \mathbf{u}(t)] + \mathbf{K}(t)(\zeta(t) - \mathbf{h}[\xi^{Est}(t)]), \quad (31)$$

where the Kalman gain $\mathbf{K}(t)$ and the state error covariance matrix $\mathbf{P}(t)$ evolve according to:

$$\begin{aligned} \mathbf{K}(t) &= \mathbf{P}(t)\mathbf{H}(t)^T\mathbf{Q}_\zeta(t)^{-1}, \\ \dot{\mathbf{P}}(t) &= \mathbf{F}(t)\mathbf{P}(t) + \mathbf{P}(t)\mathbf{F}(t)^T - \mathbf{K}(t)\mathbf{H}(t)\mathbf{P}(t) + \mathbf{Q}_\xi(t). \end{aligned} \quad (32)$$

4.3. Prediction of relative foil-fluid velocity

The implementation of advanced control strategies for cyclorotor WECs, aimed at maximizing wave power absorption (Arredondo-Galeana et al., 2024; Ermakov et al., 2022a,b; Stasinopoulos et al., 2025a), requires accurate prediction of the relative foil-fluid velocity $\mathbf{V}_F$. In this study, the proposed predictor is based on a LSTM Recurrent Neural Network (RNN), following the approach proposed in (Stasinopoulos et al., 2025c). Machine learning methods, and especially Artificial Neural Networks (ANNs), are increasingly used for prediction tasks involving highly nonlinear and complex systems. ANNs have already been successfully applied to traditional point-absorber WECs to improve control strategies and enhance energy capture (Valério et al., 2008; Li et al., 2018). LSTM networks, a specialized class of RNNs, are especially well-suited for sequence prediction tasks, due to their ability to retain long-term dependencies, while filtering out irrelevant information. In the context of wave energy, LSTM RNNs have shown promising results in forecasting wave height (Barclay and Kamranzad, 2025), wave

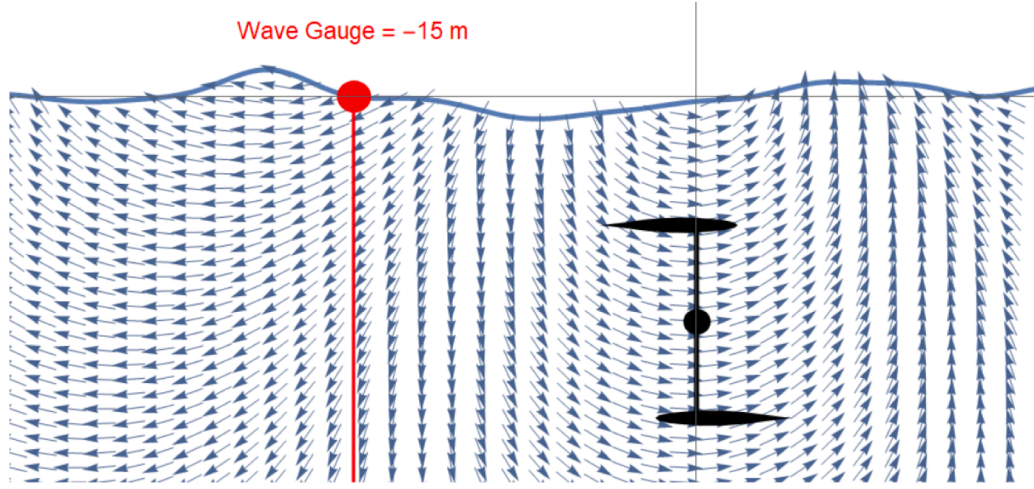


Fig. 8. Irregular wave-induced fluid velocity vector field, cyclorotor WEC, and location of the up-wave free surface elevation gauge.

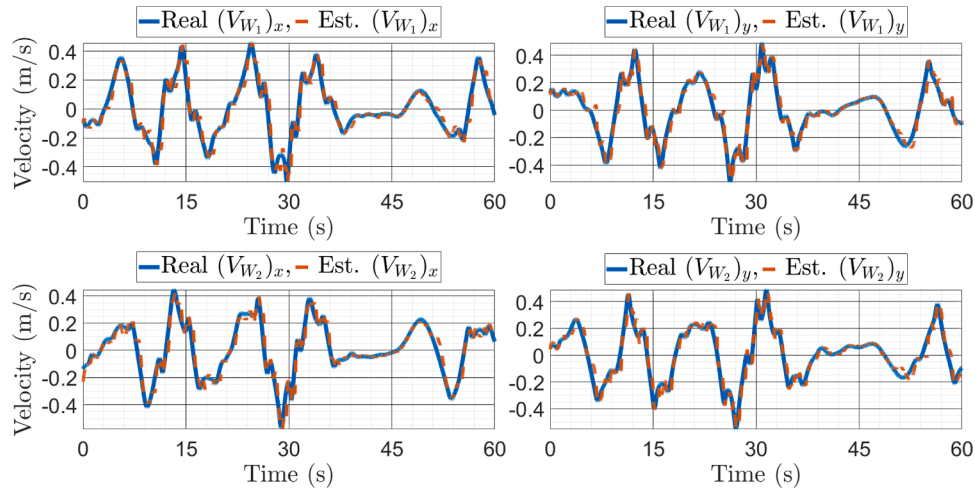


Fig. 9. Comparison between the actual and estimated x and y components of the wave-induced fluid velocity vector $\mathbf{V}_W$ for both hydrofoils, assuming a 5% model error and a 10% sensor error, for a moderate irregular sea state, with $T_p = 10$ s and $H_s = 2$ m.

Table 2

Inputs and outputs of the LSTM RNN.

Inputs:	$(\mathbf{V}_{W_1})^{[t-(\Delta t_{pred} n_{in}), \dots, t]}, (\mathbf{V}_{W_2})^{[t-(\Delta t_{pred} n_{in}), \dots, t]}, \eta^{[t-(\Delta t_{pred} n_{in}), \dots, t]}$
Outputs:	$(\mathbf{V}_{W_1})^{[t+(\Delta t_{pred}), \dots, t+(\Delta t_{pred} n_{out})]}, (\mathbf{V}_{W_2})^{[t+(\Delta t_{pred}), \dots, t+(\Delta t_{pred} n_{out})]}$

power output (Mousavi et al., 2021; Ni, 2021), and wave-induced excitation forces (Zhang et al., 2024).

The developed LSTM RNN-based predictor for the cyclorotor WEC receives as inputs the n_{in} most recent estimated values of the wave-induced fluid velocity $\mathbf{V}_W$, along with measurements of free surface elevation η from a wave gauge located up-wave (see Fig. 8). The predictor outputs the next n_{out} predicted values of the wave-induced fluid velocity $\mathbf{V}_W$. The inputs and outputs of the LSTM RNN are summarized in Table 2.

4.4. Nonlinear model predictive control (NMPC)

To maximize power production from cyclorotor WECs, using various pitch and angular velocity actuation strategies, this work adopts a NMPC approach. MPC is an advanced method that optimizes control inputs in real time based on predicted system behavior, while explicitly accounting for operational constraints. Although linear MPC performs

well in the control of traditional WECs (Faedo et al., 2017), it cannot adequately handle the strong nonlinearities present in the cyclorotor WEC model described in Section 2. Therefore, a nonlinear extension of MPC (NMPC) becomes necessary (Stasinopoulos et al., 2025a,b).

In this research, both the angular velocity and the pitch angles are manipulated, enabling maximum wave power extraction (Ringwood and Ermakov, 2022; Stasinopoulos et al., 2025a,b). In this approach, all fast control actuators are manipulated simultaneously to capture complex interactions and optimize the performance of the cyclorotor WEC. Following the strategy in (Ermakov et al., 2022a; Ringwood and Ermakov, 2022; Stasinopoulos et al., 2025a,b), the rotor angular velocity is bounded by $(0.2H_s + 0.6)\omega_p \leq \dot{\theta} \leq (0.2H_s + 1)\omega_p$, and the hydrofoil pitch angles are constrained within $-15^\circ \leq \{\gamma_1, \gamma_2\} \leq 15^\circ$. However, for sea states with shorter peak periods ($T_p = 6$ s and $T_p = 8$ s), the defined constraints on angular velocity would lead to excessively large Reynolds numbers for the hydrofoils, significantly exceeding the range covered by the experimentally measured coefficient tables (Sheldahl and Klimas, 1981) used in this model. To ensure consistency with the reference tables and avoid extrapolation beyond their validated range, an additional empirical constraint on the angular velocity is imposed, such that $\dot{\theta} \leq 0.4\pi$. This upper limit maintains the Reynolds numbers within the domain of the reference tables and prevents unrealistic results.

The optimization problem to be treated within the NMPC framework is formulated by combining the mathematical models presented in [Section 2](#) and targeting the performance function defined in [Section 3](#), specifically in [Eq. \(21\)](#). The NMPC cost function and constraints are therefore formulated as follows:

$$\begin{aligned} \min_{\dot{\theta}(t), \gamma_1(t), \gamma_2(t)} \quad & J = \frac{1}{T_0} \int_0^{T_0} (-\mathcal{T}_{PTO}(t)\dot{\theta}(t) + \mu \Delta \mathcal{T}_{PTO}^2(t)) dt, \\ \text{s.t.} \quad & (0.2H_s + 0.6)\omega_p \leq \dot{\theta}(t) \leq (0.2H_s + 1)\omega_p, \quad \dot{\theta}(t) \leq 0.4\pi, \\ & -15^\circ \leq \{\gamma_1(t), \gamma_2(t)\} \leq 15^\circ. \end{aligned} \quad (33)$$

The actuation responses of the cyclorotor WEC are evaluated based on the current state of the cyclorotor, which is estimated using the estimator introduced in [Subsection 4.2](#), and on prediction of wave-induced fluid velocity variations, generated by the predictor described in [Subsection 4.3](#).

The NMPC framework is implemented in MATLAB using the MPC Toolbox ([The MathWorks, 2024](#)), which is successfully applied to control conventional WECs in previous studies ([Richter et al., 2013, 2014](#)), as well as in the context of cyclorotor WECs ([Stasinopoulos et al., 2025a,b](#)). This toolbox is well suited for handling the strong nonlinearities inherent in the system model. The underlying optimization problem is solved using a Sequential Quadratic Programming (SQP) algorithm, as implemented in MATLAB `fmincon` solver ([The Mathworks, 2024](#)).

5. Evaluation of realistic cyclorotor WEC performance

To evaluate the performance of the developed realistic control system, the cyclorotor WEC design proposed by Atargis in ([Siegel, 2014](#)) is adopted for all numerical simulations. This design is selected since it represents the most advanced prototype currently available. The rotor has a radius of $R = 6$ m, with its shaft located at a depth of $y_0 = -12$ m below the free surface. It is equipped with two NACA0015 hydrofoils, each with a chord length of $C = 5$ m and a sectional mass of $m = 1000$ kg/m ([Arredondo-Galeana et al., 2024, 2023b](#)).

5.1. Assessment of the developed estimator accuracy

The accuracy of the proposed estimator is evaluated for two irregular sea states, following the approach in ([Stasinopoulos et al., 2025c,b](#)): The first is a moderate irregular sea state, denoted SS_1 , with a peak period of $T_p = 10$ s and a significant wave height of $H_s = 2$ m, consistent with the design conditions used for the CycWEC configuration in ([Siegel, 2019](#)). The second is a more energetic irregular sea state, denoted SS_2 , with a peak period of $T_p = 14$ s and a significant wave height of $H_s = 4$ m, thereby covering a representative range of sea states typically considered for cyclorotor operation (see [Figs. 3 and 4](#)). A discretisation time-step of $\Delta t_e = 0.0039$ s is chosen, corresponding to the sensor sampling frequency used in the LiftWEC scaled prototype experimental tests ([Ermaikov et al., 2023b,a,c](#)). The cyclorotor WEC is assumed to operate in free wave-induced rotation mode, with neutral pitch angles $\gamma_1 = \gamma_2 = 0$ and zero PTO torque, $\mathcal{T}_{PTO} = 0$. A model output noise uncertainty of 5% is applied to $w(t)$, and a measurement noise uncertainty of 10% is applied to $v(t)$. The EKF is implemented in MATLAB.

The simulation results, presented in [Figs. 9 and 10](#), show good agreement between the actual and estimated wave-induced fluid velocity components in the x and y directions, for both hydrofoils, and for both irregular sea states considered.

However, in order to numerically evaluate the accuracy of wave-induced fluid velocity estimation using the developed EKF, the Normalized Root Mean Square Accuracy (NRMSA) is selected as the performance metric. This choice is motivated by its application in previous studies assessing excitation force estimation accuracy for traditional point-absorber WECs ([Peña-Sanchez et al., 2020; Cunningham et al., 2019](#)).

Table 3

Normalized Root Mean Square Accuracy (NRMSA) of estimated wave-induced fluid velocity components at different sensor noise levels, for a moderate irregular sea state, with $T_p = 10$ s and $H_s = 2$ m.

Noise error [%]	2.5	5	10
$(V_{W_1})_x$	0.97	0.9571	0.9368
$(V_{W_1})_y$	0.9709	0.9577	0.9388
$(V_{W_2})_x$	0.9708	0.9572	0.9397
$(V_{W_2})_y$	0.9741	0.957	0.9381

Table 4

Normalized Root Mean Square Accuracy (NRMSA) of estimated wave-induced fluid velocity components at different sensor noise levels, for a more energetic irregular sea state, with $T_p = 14$ s and $H_s = 4$ m.

Noise error [%]	2.5	5	10
$(V_{W_1})_x$	0.959	0.9403	0.914
$(V_{W_1})_y$	0.9563	0.9424	0.9171
$(V_{W_2})_x$	0.955	0.9415	0.9142
$(V_{W_2})_y$	0.9549	0.9408	0.9174

The NRMSA is defined as:

$$NRMSA = 1 - \frac{\sqrt{\frac{1}{L_s - N_s + 1} \sum_{i=N_s}^{L_s} (\xi_i - \xi_i^{Est})^2}}{\max_{i \in [N_s, L_s]} \xi_i - \min_{i \in [N_s, L_s]} \xi_i}, \quad (34)$$

where L_s is the total number of samples in the simulation, and N_s is the initial sample length considered for evaluation. In this study, the first sample is set to $N_s = 0.6L_s$, following ([Peña-Sanchez et al., 2020](#)), which is sufficient to exclude the transient response and ensure steady-state behavior of the EKF. The estimated and real values of fluid velocity are represented with ξ and ξ^{Est} , respectively.

The NRMSA values for the estimated wave-induced fluid velocity components under three different sensor noise levels are presented in [Tables 3 and 4](#). For both irregular sea states, the first case corresponds to a 2.5% sensor error, the second to a 5% sensor error, and the third to a 10% sensor error. The results demonstrate that the proposed estimator maintains high accuracy across all scenarios, with NRMSA values consistently exceeding 0.93 for SS_1 and 0.91 for SS_2 , even at the highest noise level of 10%. As expected, estimation accuracy decreases slightly as sensor noise increases; however, this degradation is gradual and remains within acceptable bounds, for both irregular sea states. Overall, the estimator exhibits strong reliability under varying sensor noise conditions and sea states.

5.2. Assessment of the developed predictor accuracy

The LSTM-based predictor is trained and tested on the estimated values of V_w obtained in [Subsection 5.1](#). The same two representative irregular sea states are used, SS_1 and SS_2 . For this test, the cyclorotor WEC operates in free wave-induced rotation mode, with neutral pitch angles ($\gamma_1 = \gamma_2 = 0$) and zero PTO torque ($\mathcal{T}_{PTO} = 0$). Additional training data is generated using surface elevation measurements from an up-wave gauge, assumed to be located 15 m upwave from the cyclorotor center along the horizontal x -axis. The cyclorotor rotation simulations are performed in MATLAB, generating a sufficient dataset for training. The dataset is normalized and partitioned into training, validation, and testing subsets, with 70%, 15% and 15% of the data, respectively.

The LSTM RNN is implemented in Python, using TensorFlow and Keras libraries ([Abadi et al., 2015](#)), which provide efficient tools for constructing and training deep learning architectures. The proposed architecture includes two bidirectional LSTM layers with 192 and 128 units, respectively, allowing the model to learn temporal dependencies in both forward and backward directions. Then, a fully connected

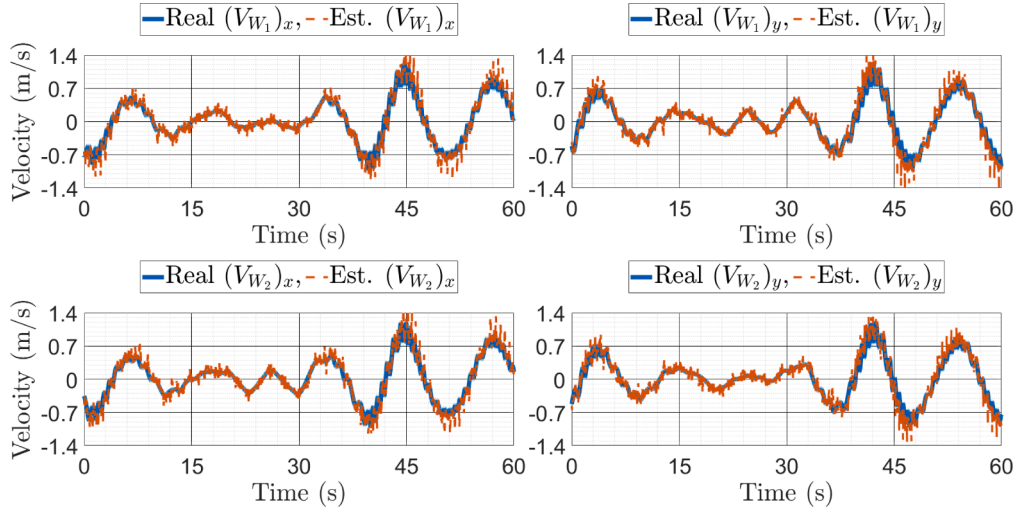


Fig. 10. Comparison between the actual and estimated x and y components of the wave-induced fluid velocity vector $\mathbf{V}_W$ for both hydrofoils, assuming a 5% model error and a 10% sensor error, for a more energetic irregular sea state, with $T_p = 14$ s and $H_s = 4$ m.

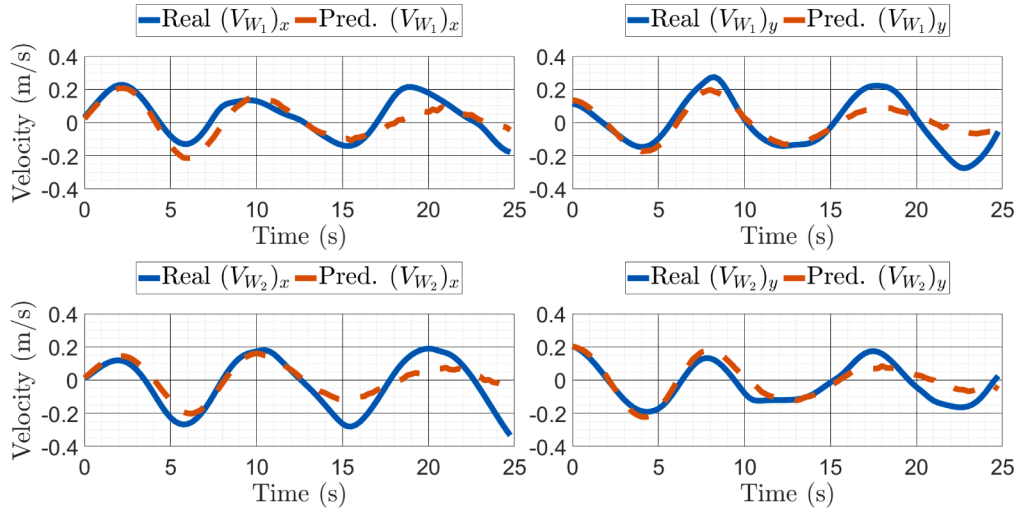


Fig. 11. Comparison between the actual and predicted x and y components of the wave-induced fluid velocity vector $\mathbf{V}_W$ for both hydrofoils, for a moderate sea state, with $T_p = 10$ s and $H_s = 2$ m.

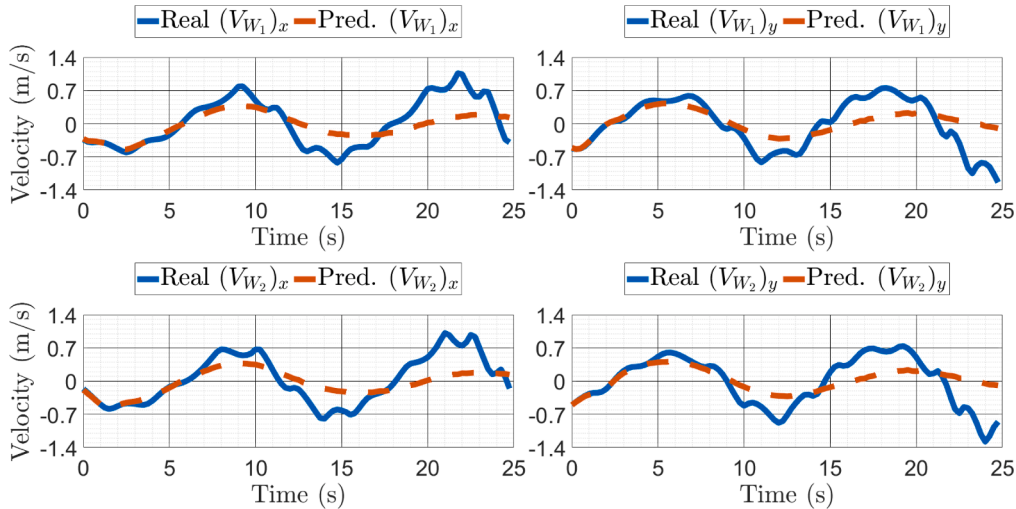


Fig. 12. Comparison between the actual and predicted x and y components of the wave-induced fluid velocity vector $\mathbf{V}_W$ for both hydrofoils, for a more energetic sea state, with $T_p = 14$ s and $H_s = 4$ m.

Table 5

NRMSE per second for each wave-induced fluid velocity component over a prediction horizon of 10 seconds, for a moderate sea state, with $T_p = 10$ s and $H_s = 2$ m.

Prediction time [s]	$(V_{W_1})_x$	$(V_{W_1})_y$	$(V_{W_2})_x$	$(V_{W_2})_y$
1	0.009	0.013	0.01	0.01
2	0.013	0.014	0.014	0.014
3	0.019	0.017	0.02	0.019
4	0.026	0.022	0.026	0.021
5	0.03	0.027	0.03	0.026
6	0.032	0.033	0.031	0.031
7	0.036	0.037	0.034	0.035
8	0.044	0.038	0.042	0.037
9	0.05	0.043	0.048	0.043
10	0.052	0.054	0.05	0.052

Table 6

NRMSE per second for each wave-induced fluid velocity component over a prediction horizon of 10 seconds, for a more energetic sea state, with $T_p = 14$ s and $H_s = 4$ m.

Prediction time [s]	$(V_{W_1})_x$	$(V_{W_1})_y$	$(V_{W_2})_x$	$(V_{W_2})_y$
1	0.01	0.014	0.011	0.011
2	0.017	0.019	0.018	0.018
3	0.023	0.020	0.025	0.023
4	0.028	0.023	0.028	0.024
5	0.031	0.028	0.031	0.028
6	0.034	0.034	0.033	0.034
7	0.041	0.042	0.039	0.042
8	0.049	0.047	0.051	0.047
9	0.052	0.051	0.054	0.051
10	0.061	0.06	0.062	0.06

(dense) layer maps the output of the bidirectional layers to the predicted wave-induced fluid velocity components for each time step in the prediction horizon. Hyperparameter tuning is conducted using Bayesian optimization, available in Optuna library in Python (Akiba et al., 2019). The final model is trained using the Adam optimizer (Kingma and Ba, 2015) with a learning rate of 0.008292 and a batch size of 64. The length of the input sequence is $n_{in} = 50$ time steps and the length of the output sequence is $n_{out} = 100$ time steps, where each time step has a duration of $\Delta t_{pred} = 0.25$ s.

Figs. 11 and 12 compare the predicted and actual values of the wave-induced fluid velocity components in the x and y directions for both hydrofoils, and for both irregular sea states considered. The results indicate that the predictor provides reliable estimates over a 12-second forecast horizon for SS_1 , and over a 8-second forecast horizon for SS_2 . To quantitatively assess the prediction accuracy of the LSTM model, the Root Mean Squared Error (RMSE) is adopted as a standard performance metric. RMSE measures the average magnitude of the prediction errors and is commonly used in forecasting tasks involving neural networks. In the context of wave energy, it is employed in several studies, including (Mousavi et al., 2021; Ni, 2021; Zhang et al., 2024), and is defined as:

$$RMSE = \sqrt{\frac{1}{N_w} \sum_{i=1}^{N_w} ((V_W)_i - (V_W^{Pred})_i)^2}, \quad (35)$$

where $(V_W)_i$ and $(V_W^{Pred})_i$ denote the ground truth and predicted values, respectively, and N_w is the prediction horizon length. The RMSE is then normalized by the range of the data to yield the Normalized Root Mean Squared Error (NRMSE), given by:

$$NRMSE = \frac{RMSE}{(V_W)^{Max} - (V_W)^{Min}}. \quad (36)$$

Tables 5 and 6 present the NRMSE values for each component of the wave-induced fluid velocity vector over a 10-second prediction horizon, evaluated at 1-second steps, for both irregular sea states. The reported

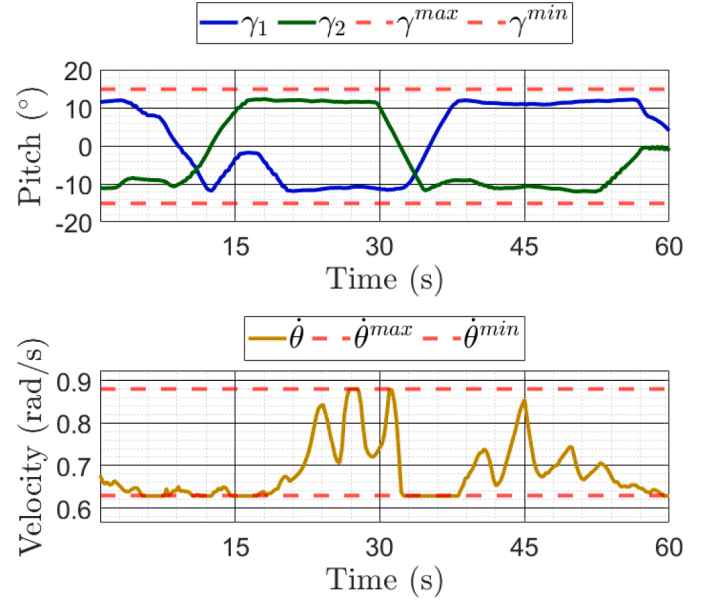


Fig. 13. Pitch angles and angular velocity time-series with active upper and lower constraints over a one-minute interval, under the proposed realistic control, for a representative irregular sea state, with $T_p = 10$ s and $H_s = 2$ m.

NRMSE values were obtained by averaging 1000 independent testing simulation sequences.

The results show that prediction accuracy is highest during the initial seconds, particularly within the first 3 seconds, where the NRMSE remains below 0.02 for SS_1 , and slightly above 0.02 for SS_2 . As expected, the NRMSE increases gradually with time, reflecting a typical decline in accuracy over longer prediction horizons. Nevertheless, the error remains within acceptable bounds, with NRMSE values staying below 0.054 throughout the full 10-second horizon for SS_1 , and below 0.062 for SS_2 . These results confirm that the predictor provides sufficient accuracy to support the implementation of advanced control strategies, such as NMPC, for a cyclorotor WEC.

5.3. Evaluation of integrated control system performance

This subsection assesses the overall performance of the developed realistic control for a cyclorotor WEC. The proposed NMPC approach, integrated with an estimator and predictor of the relative foil-fluid velocity, is tested across a range of irregular sea states, selected to be representative of the wave conditions in the two ocean regions considered in this study, acquired from ERA5 for the year 2024 and shown in Figs. 3 and 4. The results are computed from simulations of one-hour cyclorotor WEC operations in each considered sea state.

All tuning parameters of the NMPC are selected following the tuning guidelines presented in (Stasinopoulos et al., 2025a,b), and kept constant across all simulations. The weighting factor in the performance function (see Eq. (33)) is set to $\mu = 10^{-5}$, while the prediction horizon is set to $t_p = 7.5$ s, with a sampling time of $T_s = 0.25$ s, which is sufficient to achieve convergence in terms of maximum wave power extraction.

Fig. 13 shows the pitch angles and angular velocity time-series with active upper and lower constraints, as defined in Section 3, over a one-minute interval, under the proposed realistic control, for a representative irregular sea state SS_1 . Fig. 13 demonstrates that the proposed control strategy effectively respects the system constraints, while responding to the wave-induced fluid dynamics.

The control performance results are expressed in terms of CWR (Eq. (22)), which is adopted as the primary wave energy conversion efficiency metric. First, the results of the idealised control, which assumes perfect knowledge of the relative foil-fluid velocity, are presented in Ta-

Table 7

Mechanical power generation in CWR [%] across sea states, assuming ideal estimation and perfect knowledge of the relative foil-fluid velocity.

$T_p =$	6 s	8 s	10 s	12 s	14 s	16 s
$H_s = 5$ m	46.71	68.59	82.21	56.16	44.28	33.51
$H_s = 4$ m	50.67	54.54	74.52	52.85	37.68	30.5
$H_s = 3$ m	51.32	57.16	59.84	42.33	38.02	26.17
$H_s = 2$ m	46.81	72.98	62.56	46.46	38.01	31.61
$H_s = 1$ m	56.01	75.46	85.09	62.06	53.35	38.09

Table 8

Mechanical power generation in CWR [%] across sea states, incorporating estimator and predictor of the relative foil-fluid velocity.

$T_p =$	6 s	8 s	10 s	12 s	14 s	16 s
$H_s = 5$ m	42.46	64.54	78.28	55.16	40.33	30.72
$H_s = 4$ m	49.01	50.32	72.45	52.36	34.34	27.54
$H_s = 3$ m	48.47	51.47	58.26	41.4	34.9	19.38
$H_s = 2$ m	40.49	71.32	57.41	42.65	36.55	28.31
$H_s = 1$ m	46.01	71.71	84.4	58.6	50.22	37.48

blue 7 for various values of significant wave height H_s and peak period T_p . The CWR values are relatively low for sea states with a short peak period ($T_p = 6$ s), across all significant wave heights, indicating poor performance in fast, steep waves. As the peak period increases, the CWR values improve significantly, reflecting a closer alignment between sea states with $T_p = 8$ s, 10 s, and 12 s and the operational characteristics of the cyclorotor WEC. The highest CWR value, 85.09%, occurs for the sea state with $T_p = 10$ s and $H_s = 1$ m. This sea state also yields high performance in (Stasinopoulos et al., 2025a) and corresponds closely to the design point of the cyclorotor WEC optimized in (Siegel, 2014). The CWR values decline again for sea states with longer peak periods, mainly because it becomes challenging to absorb all of the available wave power.

In contrast, the results obtained for the realistic control, which incorporates an estimator and predictor of the relative foil-fluid velocity, are shown in Table 8. The general trend remains similar to that of the idealised case. However, as expected, some power losses occur compared to the idealised case, due to inaccuracies in estimation and prediction. The best performance is observed for the same sea state as in the idealised case, with a CWR of 84.4%.

The relative difference in CWR between the idealised and the realistic case is presented in Table 9. This analysis quantifies the reduction in energy capture due to inaccuracies in estimation and prediction. The relative differences are generally small, confirming that estimation and prediction errors introduce modest power loss. The greatest power loss occurs for the sea state with peak period $T_p = 16$ s and significant wave height $H_s = 3$ m, where a relative difference of 25.95% is observed between idealised and realistic CWR. On the contrary, the smallest power loss of 0.81% is observed for the sea state with $T_p = 10$ s and significant wave height $H_s = 1$ m. The average power loss across all sea states is approximately 7%, which is within an acceptable range. This demonstrates that integrating the developed estimator and predictor within a NMPC maintains reliable performance, especially for the sea states with higher probability of occurrence, and validates its effectiveness under realistic operating conditions.

The annual mechanical energy production, under the idealised and realistic control strategies, is calculated using Eq. (23), with results for Humboldt Bay, USA, and the North Atlantic coast of France (Section 3) compared in Table 10. The overall loss due to estimation and prediction inaccuracies is just under 6% for both regions, providing realistic estimates of the total annual mechanical energy production of a cyclorotor WEC for the first time. Using the proposed realistic control, the annual mechanical energy production is 95.98 MWh per hydrofoil span meter for Humboldt Bay and 70.27 MWh/m for the Bay of Biscay, values very

Table 9

Relative difference in CWR [%] across sea states between the idealised and the realistic case.

$T_p =$	6 s	8 s	10 s	12 s	14 s	16 s
$H_s = 5$ m	9.1	5.9	4.78	1.78	8.92	8.33
$H_s = 4$ m	3.28	7.74	2.78	0.93	8.86	9.7
$H_s = 3$ m	5.54	9.95	2.64	2.2	8.21	25.95
$H_s = 2$ m	13.5	2.27	8.23	8.2	3.84	10.44
$H_s = 1$ m	17.85	4.97	0.81	5.58	5.87	1.6

close to those reported for the same sea regions in (Siegel, 2014) and (Arredondo-Galeana et al., 2024; Devoy McAuliffe et al., 2024), respectively. Atargis reported 90.5 MWh/m annual electrical energy production for Humboldt Bay, assuming 95% generator efficiency, corresponding to 95.26 MWh/m mechanical energy production, while the LiftWEC project reported 66.68 MWh/m for Bay of Biscay (Ermakov and Ringwood, 2022). These earlier studies, however, assumed perfect knowledge of relative foil-fluid velocity, relied on past ocean data, and employed alternative performance metrics, control methods, and solution spaces. Nevertheless, the present performance assessment results validate and even slightly improve the performance predictions for cyclorotor WEC technology previously conducted by the Atargis Corporation and the LiftWEC project, despite accounting for losses, owing to the more advanced control strategy. In particular, the new annual energy production estimate for the Bay of Biscay represents an improvement of approximately 5.4% over LiftWEC, which could translate into a significant reduction of the LCoE reported in (Devoy McAuliffe et al., 2024), assuming the same operational cost. Furthermore, the proposed realistic control is shown to achieve significant annual energy production while keeping estimation and prediction inaccuracies within acceptable limits.

Table 10

Idealised and realistic total annual mechanical energy production for different locations in MWh/m.

Wave climate location	Idealised control	Realistic control
Humboldt Bay (see Fig. 3)	101.57	95.98
Bay of Biscay (see Fig. 4)	74.21	70.27

6. Conclusions and discussion

This paper presents the first realistic control philosophy for cyclorotor WECs. The proposed approach integrates a nonlinear model predictive controller with an estimator and a predictor for relative foil-fluid velocity, and is implemented and tested across a wide range of irregular sea states, using the most advanced cyclorotor WEC prototype design. The estimator and predictor are assessed independently, demonstrating accurate tracking and forecasting of the relative foil-fluid velocity, and providing a solid foundation for the integrated control system. Performance assessments of the combined predictor-estimator-NMPC loop show that the realistic controller achieves performance close to that of the idealised case. The average reduction in CWR due to estimation and prediction inaccuracy is approximately 7%, across all sea states, with annual mechanical energy production losses limited to less than 6% in two representative sea regions. These values remain within acceptable limits, confirming both the robustness and the practical feasibility of the proposed approach.

For the first time, realistic estimates of annual mechanical energy production are obtained for two key locations proposed for potential cyclorotor WEC installation: Humboldt Bay and the Bay of Biscay. The performance predictions reported in this study are consistent with previous results, which were based on idealised assumptions. Furthermore, even when accounting for potential losses due to prediction and estimation inaccuracy, the assessed performance is improved, owing to the more advanced control and actuation strategies proposed in this work.

These findings confirm and validate the ability of cyclorotor WECs to deliver competitive annual performance under realistic operating conditions.

At present, the implementation of the proposed control system does not yet achieve real-time performance, primarily due to the computational cost associated with the combined execution of the estimator and NMPC in MATLAB, together with the data-driven predictor in Python. All simulations are performed on a 64-bit desktop system equipped with a 13th Gen Intel(R) Core(TM) i9-13900 processor (2.00 GHz) and 32 GB RAM. Under this configuration, and with the present interpreted, non-compiled implementation, the combined estimator-predictor-NMPC execution time is approximately 14.3 s, which significantly exceeds the adopted control timestep of 0.25 s.

The reported execution time reflects software, rather than algorithmic, limitations. A fully compiled implementation in C/C++ is expected to reduce computation time significantly and likely enable real-time feasibility. In addition, the predictor is developed in Python, and must therefore be executed through a MATLAB-Python interface, which further increases the overall computation overhead. As an alternative pathway towards real-time implementation, numerical solutions, obtained using the proposed control approach, can be used to train a neural network for the development of a physics-informed neural network based control strategy (Zhan and Ringwood, 2024). Nevertheless, the present study demonstrates the potential of the proposed realistic energy-maximising control, while real-time implementation is identified as an important direction for future work.

While energy-maximising control can have adverse effects on some traditional WECs, in particular through increased force, displacement and velocity (Ziaei et al., 2024), cyclorotor WECs have a somewhat unique characteristic: the average velocity and overall displacement of cyclorotor WECs are independent of control actions (Ermakov et al., 2022a). However, force modulation of the shaft may induce additional loading on the foil actuation points, and, consequently, on the device structure. This effect was considered in (Arredondo-Galeana et al., 2024), where significant load reduction was achieved with minimal loss in energy capture. An additional consideration relates to the parasitic energy consumption associated with pitch actuation, which should be investigated in future work. In relation to the capital cost of advanced control, including pitch actuation, there is an additional cost of pitch servos, and associated maintenance costs (Devoy McAuliffe et al., 2024).

Although extreme sea states are not considered for the proposed realistic control for cyclorotor WECs (see Figs. 3 and 4), the cyclorotor WEC has an advantage over many other types of WECs in such conditions. Cyclorotor WEC can either (a) submerge to preserve a uniform level of wave excitation (Ermakov and Ringwood, 2021b; Energy, 2025) or (b) if submergence is not available, brakes can be used to stop the device rotation, and maintaining the hydrofoil pitches in neutral position prevents the generation of significant lift forces that could otherwise induce renewed rotation and increased structural loading (Ermakov et al., 2022a). Of course (a) is preferable, since power production continues. Model mismatch is not considered in the current study. Future work should focus on examining sensitivity and robustness of the proposed realistic control for cyclorotor WECs, as well as developing fault-tolerant control strategies (Zhang et al., 2022; Gonzalez-Esculpi et al., 2023; Pardini et al., 2024; Said et al., 2025).

Further limitations of the present study include the assumption of model output error in the estimator, which may not capture all sources of uncertainty, as well as the use of an analytical mathematical model, which may not capture more complex hydrodynamic effects. Furthermore, no pitch actuation and PTO system are included, which could account for pitch position and torque errors, respectively, in a practical control scheme. Despite these limitations, the implementation and testing of the first realistic control for cyclorotor WECs can be considered successful. Future research could extend the framework to incorporate more comprehensive uncertainty quantification and validation against experimental data.

CRedit authorship contribution statement

Ilias Stasinopoulos: Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization; **Andrei M. Ermakov:** Writing – original draft, Supervision, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization; **John V. Ringwood:** Writing – review & editing, Supervision, Funding acquisition, 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.

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