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POWER-Net: Predictive Optimization and Wave Energy Regulation in Networked WEC Systems

Zahra Hashemi[a][1], Dipankar Maity[a], Artur Wolek[a]

[a]*University of North Carolina at Charlotte, Charlotte, NC 28223, USA*

Abstract

This work presents a control framework for maximizing energy extraction in arrays of wave energy converters (WECs) operating in hydrodynamically coupled environments. Each WEC's motion influences others through radiated wave interactions, making coordinated control essential. We model the coupled dynamics using Cummins' equation and design a centralized controller that computes optimal control inputs for all WECs based on collective state information. To reduce communication burden, we investigate an event-triggered communication strategy where WECs transmit sensor data only when necessary. We analyze the impact of communication frequency on energy capture and quantify the trade-off between communication overhead and performance. Simulation results show that intermittent communication can achieve near-optimal power extraction while significantly reducing communication requirements.

Keywords: Wave Energy Converters; Energy Maximization; Event-Triggered Communication; Linear Quadratic Regulator.

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1 Introduction

Ocean wave energy represents a vast and largely untapped source of renewable energy. Among the various conversion technologies, WECs are considered a promising approach for harnessing energy from ocean waves. However, the high cost of deployment and limited energy extraction efficiency, particularly when compared to mature technologies like wind and solar, remain major obstacles to widespread commercialization [1]. One strategy to reduce installation costs and enhance economic viability is to deploy WECs in arrays rather than as standalone units.

In array-based deployments of WECs, close spacing can result in destructive hydrodynamic interactions that diminish overall energy capture. However, recent work has shown that centralized and cooperative control strategies can mitigate these interactions by coordinating device motions [2, 3]. Model Predictive Control (MPC) and other optimal control methods have been extensively explored for individual WECs and arrays, often emphasizing power maximization under physical constraints such as displacement and reactive power limitations [4, 5, 6, 7, 8].

[1]* Zahra Hashemi

E-mail address: zahrahashemi1@charlotte.edu

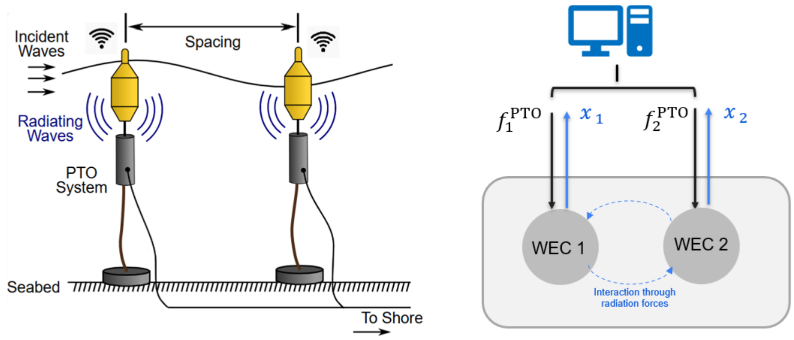


Figure 1: Illustration of centralized control for a two-WEC array. **(Left)** WECs interact through radiating waves. **(Right)** A centralized controller receives state measurements x_1 and x_2 and generates PTO forces f_1^{PTO} and f_2^{PTO}.

Nonetheless, most existing approaches assume continuous communication among devices and controller or ignore communication constraints altogether. This assumption becomes impractical for large-scale deployments where real-time data transmission is limited by bandwidth, latency, or energy cost. To address this challenge, the control community has developed a variety of event-triggered and communication-aware strategies, particularly for linear systems [9, 10, 11, 12]. These methods demonstrate how intermittent feedback can be leveraged to maintain performance while significantly reducing communication.

In this work, we propose a communication-aware control framework for WEC arrays that integrates a discrete-time linear quadratic regulator (LQR) design with an event-triggered communication strategy. Unlike periodic or continuous feedback systems, our method jointly optimizes control inputs and transmission schedules, enabling the system to make informed trade-offs between estimation accuracy and communication cost. Furthermore, we conduct a detailed trade-off analysis that quantifies how reducing communication frequency impacts the extracted energy performance, providing actionable insights for practical deployment of networked WEC systems.

2 Problem Formulation

We formulate a control problem for a system of two heaving point absorber Wave Energy Converters, which are hydrodynamically coupled through radiation and diffraction effects (see Fig. 1(Left)). The objective is to design an optimal control strategy that maximizes the total extracted mechanical power over a finite time horizon, while respecting the coupled system dynamics. Departing from traditional formulations, this work models the interaction between devices, including cross-radiation and diffraction effects. We begin with Cummins' equation [2], which describes the vertical (heave) motion of a single WEC in an array:

$$m_i \ddot{p}_i(t) = f_i^{\mathrm{exc}}(t) + f_i^{\mathrm{r}}(t) + f_i^{\mathrm{h}}(t) + f_i^{\mathrm{PTO}}(t), \tag{1}$$

where m_i is the mass of the i-th buoy, $p_i(t)$ is its heave displacement, and $f_i^{\mathrm{exc}}(t)$, $f_i^{\mathrm{r}}(t)$, $f_i^{\mathrm{h}}(t)$, and $f_i^{\mathrm{PTO}}(t)$ denote the excitation, radiation, hydrostatic, and power take-off (PTO) forces acting on the i-th WEC, respectively, at time t.

The hydrostatic restoring force and radiation force can be expressed as [2]:

$$f_i^{\mathrm{h}}(t) = -k_i^h \, p_i(t), \qquad f_i^{\mathrm{r}}(t) = -\mu_i \, \ddot{p}_i(t) - \sum_{j=1}^{2} \int_0^t K_{ij}^r(t-\tau)\, \dot{p}_j(\tau)\, \mathrm{d}\tau, \tag{2}$$

where k_i^h is the hydrostatic stiffness coefficient for the i-th WEC, μ_i is its added mass at infinite frequency, and $K_{ij}^r(\cdot)$ is the radiation impulse response function representing the hydrodynamic coupling from WEC j to WEC i. To improve computational efficiency, the radiation force can be approximated using a linear state-space model with additional states $x_{r_{ii}}$ and $x_{r_{ij}}$ [4]. By defining the state vector for each WEC as

$$x_i = \begin{bmatrix} p_i & \dot{p}_i & x_{r_{ii}}^\top & x_{r_{ij}}^\top \end{bmatrix}^\top, \tag{3}$$

where $x_{r_{ii}} \in \mathbb{R}^{n_{ii}}$ represents the internal states capturing the *self-radiation* effects of WEC i, and $x_{r_{ij}} \in \mathbb{R}^{n_{ij}}$ models the *cross-radiation* effect from WEC j to WEC i. Notably, $x_{r_{ij}}$ depends on the motion of WEC j, which necessitates the inclusion of a coupling term $A_{ij}x_j$ in the state-space representation of $\dot{x}_i$. For a detailed derivation of this modeling approach, refer to [3]. we may rewrite the dynamics of each WEC in the array in the following state-space form:

$$\dot{x}_i = A_i x_i + B_i u_i + A_{ij} x_j + B_i^{\mathrm{exc}} f_i^{\mathrm{exc}}(t) + w_i^d(t), \quad \text{for } i \neq j, \tag{4}$$

where u_i is the control input (i.e., $f_i^{\mathrm{PTO}}(t)$), A_i and B_i are the local system matrices for the i-th WEC, and A_{ij} captures the hydrodynamic coupling from WEC j to WEC i. The term $f_i^{\mathrm{exc}}(t)$ represents the wave excitation force acting on the i-th WEC. The term $w_i^d(t)$ accounts for unmodeled dynamics and environmental uncertainties, including wave prediction errors and approximations in the radiation model.

To facilitate coordinated control, the dynamics of both WECs are combined into a centralized state-space model:

$$\dot{x}(t) = Ax(t) + Bu(t) + B^{\text{exc}} f^{\text{exc}}(t) + B_d w^d(t), \tag{5}$$

with an augmented state vector $x(t) \in \mathbb{R}^n$, where $n = n_1 + n_2$ and each WEC contributes n_i states. For WEC 1, $n_1 = 2 + n_{11} + n_{12}$, corresponding to 2 states for heave position and velocity, n_{11} self-radiation states, and n_{12} radiation states due to interaction with WEC 2. Similarly, for WEC 2, $n_2 = 2 + n_{22} + n_{21}$, where n_{22} and n_{21} represent self- and cross-radiation states, respectively.

$$x(t) = \begin{bmatrix} p_1 & \dot{p}_1 & x_{r11}^\top & x_{r12}^\top & p_2 & \dot{p}_2 & x_{r21}^\top & x_{r22}^\top \end{bmatrix}^\top, \tag{6}$$

where p_1 and $\dot{p}_1$ represent the heave position and velocity of WEC 1, p_2 and $\dot{p}_2$ represent those of WEC 2, and the remaining components correspond to internal radiation states that capture both self-radiation and cross-coupling effects. The control input vector $u(t) \in \mathbb{R}^2$ is the concatenated PTO forces:

$$u(t) = \begin{bmatrix} f_1^{\text{PTO}}(t) & f_2^{\text{PTO}}(t) \end{bmatrix}^\top. \tag{7}$$

The system matrices $A \in \mathbb{R}^{n\times n}$ and $B \in \mathbb{R}^{n\times 2}$ capture the full coupled dynamics in (5), including local radiation effects and cross-radiation interactions. A detailed derivation of this high-order hydrodynamic model is provided in [3]. The formulation used here represents a reduced order realization tailored for the development of *POWER-Net*: a predictive optimization and wave energy regulation framework for networked WEC systems. The mechanical power extracted by each WEC is modeled as the product of the corresponding PTO force and the heave velocity [2]. The total extracted energy over the finite horizon $[0, T]$ is given by:

$$P_{\text{total}} = \mathbb{E}\Big[\int_0^T \Big(-f_1^{\text{PTO}}(t)\,\dot{p}_1(t) - f_2^{\text{PTO}}(t)\,\dot{p}_2(t)\Big)\,\mathrm{d}t\Big] = 2\mathbb{E}\Big[\int_0^T x(t)^\top N u(t)\mathrm{d}t\Big], \tag{8}$$

where

$$N = \begin{bmatrix} 0 & -0.5 & \mathbf{0}_{n_{11}} & \mathbf{0}_{n_{12}} & 0 & 0 & \mathbf{0}_{n_{21}} & \mathbf{0}_{n_{22}} \\ 0 & 0 & \mathbf{0}_{n_{11}} & \mathbf{0}_{n_{12}} & 0 & -0.5 & \mathbf{0}_{n_{21}} & \mathbf{0}_{n_{22}}^\top \end{bmatrix}^\top.$$

Here, $\mathbf{0}_n$ denotes a row vector of zeros of dimension $1 \times n$. The total energy maximization problem is an optimal control problem whose solution is known to be a *state feedback law* [13]. That is, the optimal input at any given time t is a function of $x(t)$, which requires sensors to continuously measure $x(t)$ and make those measurements available to the controller at all times. In scenarios where the controller is remotely located—such as in a WEC farm, where computation is performed at a (possibly remote) centralized controller (see Fig. 1(right))—continuous communication between the WECs' sensors and the centralized controller is required.

The primary objective of this work is to student how communication constraints can affect the WECs' performance. In particular, we consider an average communication constraint of the following form:

$$\tfrac{1}{T}\mathbb{E}[m(T)] \leq \bar{m}, \tag{9}$$

indicating that the average number of communication per unit of time is bounded by $\bar{m}$. Here, $m(T)$ denotes the total number of communication during the operation interval $[0, T]$ between the sensors and the centralized controller. The communication constrained optimization problem is challenging to solve, and therefore, we formulate a relaxation of this problem:

$$J = P_{\text{total}} + \lambda_1 \tfrac{1}{T}\mathbb{E}[m(T)],$$

where $\lambda_1 > 0$ is a regularization parameter balancing the power and communication trade-off. In this work, we study *when* to communicate and *how* to control the PTO to optimize the performance metric J.

3 Solution Approach

We use a linear quadratic optimal control approach in this paper. Here we modify the cost function to consider the form

$$J_1 = \mathbb{E}\Big[\int_0^T \left(x^\top(t)Qx(t) + u^\top(t)Ru(t) + 2x^\top(t)Nu(t)\right)\mathrm{d}t + x_T^\top Q_f x_T + \lambda m(T)\Big], \tag{10}$$

where $\lambda = \frac{\lambda_1}{T}$ and where we added the two terms $x^\top(t)Qx(t)$ and $u^\top(t)Ru(t)$—with Q and R being positive semi-definite and positive definite, respectively— to enforce strict convexity to the problem and obtain a well-defined solution to the problem. In an operational standpoint, these two extra terms penalizes the WEC motion and control effort, respectively.

For real-time digital implementation of the control law, the continuous-time model is discretized using a zero-order hold with sampling time T_s, resulting in a discrete-time system with matrices A_d and B_d (i.e., $A_d = e^{AT_s}$, $B_d = \left(\int_0^{T_s} e^{A\tau}\mathrm{d}\tau\right)B$). In the discrete-time setting, the continuous time variable $t \in [0, T]$ is replaced by the discrete index $k \in \{0, 1, \ldots, N\}$, where $t = kT_s$ and $T = NT_s$. This enables the application of a discrete-time LQR with a finite horizon, which is well established in the optimal control literature [13]. The discrete-time framework also facilitates integration with event-triggered communication strategies, which are crucial in networked systems where bandwidth or power is limited.

The optimal control input without any communication constraint is given as [13]

$$u_k = -S_k^{-1}G_k x_k - S_k^{-1}B_d^\top P_{k+1}B_d^{\text{exc}} f_k^{\text{exc}} - S_k^{-1}B_d^\top \eta_{k+1}, \tag{11}$$

where the matrices are computed via backward recursion:

$$P_k = Q + A_d^\top P_{k+1}A_d - (N + A_d^\top P_{k+1}B_d)\,S_k^{-1}\,(N + A_d^\top P_{k+1}B_d)^\top, \qquad P_N = Q_f, \tag{12}$$

$$\eta_k = \left(A_d^\top - G_k^\top S_k^{-1}B_d^\top\right)\eta_{k+1} + \left(A_d^\top P_{k+1} - G_k^\top S_k^{-1}B_d^\top P_{k+1}\right)B_d^{\text{exc}} f_k^{\text{exc}}, \qquad \eta_N = 0, \tag{13}$$

$$G_k = N + A_d^\top P_{k+1}B_d, \qquad S_k = R + B_d^\top P_{k+1}B_d. \tag{14}$$

Here, the first term $L_k = S_k^{-1}G_k$ represents the discrete-time LQR feedback gain, while the remaining terms account for wave excitation and co-state dynamics, enabling the controller to anticipate disturbances and enhance robustness. Since the wave excitation profile f^{exc} is assumed to be known a priori (e.g. by forecasting), the associated control-affine terms can be precomputed offline. However, evaluating the full control law still requires real-time access to the state of the system. This poses a communication challenge in distributed WEC arrays, where continuous-state transmission is often impractical due to bandwidth and energy constraints.

To address this, we adopt a communication-aware control strategy based on event-triggered transmission, inspired by Molin et al. [14]. A binary decision variable $\theta_k \in \{0, 1\}$ is introduced at each discrete time step k, where $\theta_k = 1$ indicates that the true system state x_k is transmitted to the controller. When $\theta_k = 0$, no new transmission occurs, and the controller relies on a locally maintained state estimate $\hat{x}_k$:

$$\hat{x}_k = \begin{cases} x_k, & \theta_k = 1, \\ A_d\hat{x}_{k-1} + B_d u_k + B_d^{exc} f_k^{\text{exc}}, & \theta_k = 0. \end{cases} \tag{15}$$

This selective transmission scheme significantly reduces communication load while maintaining acceptable control performance. The communication schedule over the prediction horizon is encoded in the binary transmission vector $\Theta = [\theta_0, \theta_1, \ldots, \theta_{N-1}]^\top$. Upon substituting the control $u_k = -S_k^{-1}G_k\hat{x}_k - S_k^{-1}B_d^\top P_{k+1}B_d^{\text{exc}} f_k^{\text{exc}} - S_k^{-1}B_d^\top\eta_{k+1}$ in (10), J becomes

$$J = J_{\text{constant}} + \mathbb{E}\left[\sum_{k=0}^{N-1} e_k^\top L_k^\top S_k L_k e_k\right] + \lambda\mathbb{E}\left[\sum_{k=0}^{N-1}\theta_k\right], \tag{16}$$

where $e_k = x_k - \hat{x}_k$ denotes the state estimation error. The term J_{constant} captures the portion of the expected cost arising from initial conditions and stochastic disturbances; it is independent of the decision variables and therefore not subject to optimization. The second term in (16) accounts for the degradation in control performance due to outdated or imprecise state estimates. The final term penalizes the number of communication events, where the weighting factor λ regulates the trade-off between control accuracy and communication cost.

Using (15) and the discrete-time version of (5), the evolution of the estimation error e_k is governed by:

$$e_{k+1} = (1 - \theta_{k+1})(A_d e_k + w_k^d). \tag{17}$$

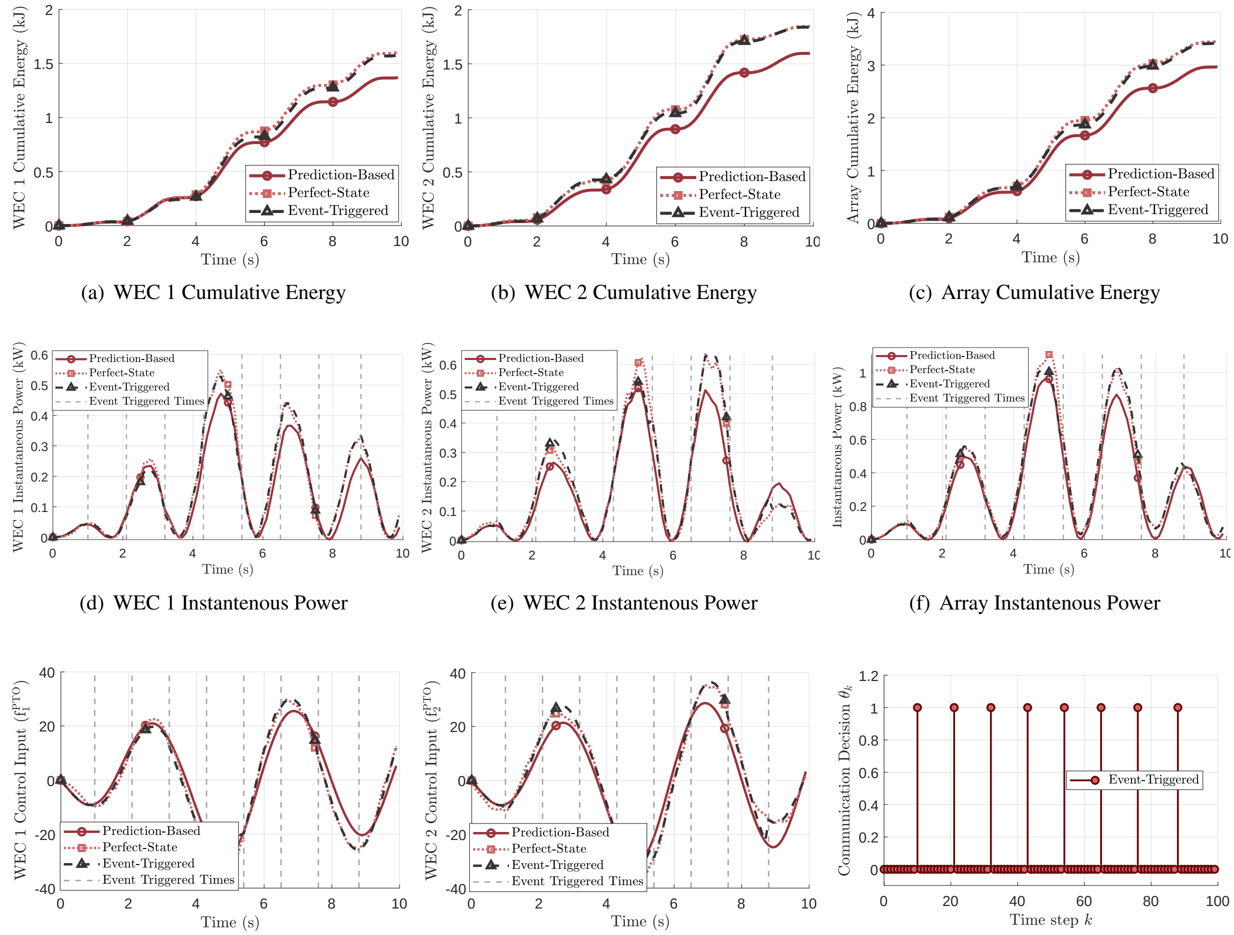
As shown in (17), a new transmission at time $k + 1$ ($\theta_{k+1} = 1$) resets the estimation error to zero. This formulation enables the controller to dynamically balance estimation accuracy against communication cost—an essential feature for WEC arrays deployed in remote marine environments with limited communication and power budgets. We therefore optimize (16) under the constraint (17) to obtain the optimal communication times between the WECs and their centralized computation unit. This results in a mixed-integer program solved using Gurobi via YALMIP.

4 Simulation Setup

We simulate a two-body WEC array (WEC 1 and WEC 2) to evaluate energy extraction under different communication strategies: *continuous*, *prediction-based*, and *event-triggered control*. Coupled WEC dynamics, including radiation, are discretized using a zero-order hold with sampling time $T_s = 0.1$ seconds. Excitation forces follow a Bretschneider spectrum with significant wave height $H_s = 1.55$ m and zero-crossing period $T_z = 5.98$ s. Process disturbance w_d is modeled as zero-mean noise with covariance $\Sigma_w = 0.2I$. A centralized LQR controller is designed for coordinated control of both WECs to maximize extracted power, using weight matrices $Q = 4I$ and $R = I$. Figure 1 (Right) illustrates the architecture, where the controller receives states from both devices and sends PTO forces. The underlying hydrodynamic model is adopted from [3], which includes radiation dynamics and coupling between WECs. The resulting augmented state vector has dimension $n = 30$, composed of heave position and velocity (2 states per WEC), self-radiation states with $n_{11} = n_{22} = 5$, and cross-radiation states with $n_{12} = n_{21} = 8$ for each WEC. We compare three communication protocols:

1. **Continuous:** Full-state feedback at every time step (ideal benchmark).
2. **Event-Triggered:** Selective transmission based on optimization (16), balancing accuracy and cost.
3. **Prediction-Only:** No communication; The controller is entirely based on model-based predictions.

These scenarios span from high-bandwidth to zero-communication control, providing insight into performance-communication trade-offs in realistic offshore deployments.



(a) WEC 1 Cumulative Energy (b) WEC 2 Cumulative Energy (c) Array Cumulative Energy

(d) WEC 1 Instantenous Power (e) WEC 2 Instantenous Power (f) Array Instantenous Power

(g) WEC 1 Control Input (h) WEC 2 Control Input (i) Communication Schedule

Figure 2: Performance comparison of centralized control for a two-WEC system under various communication strategies.

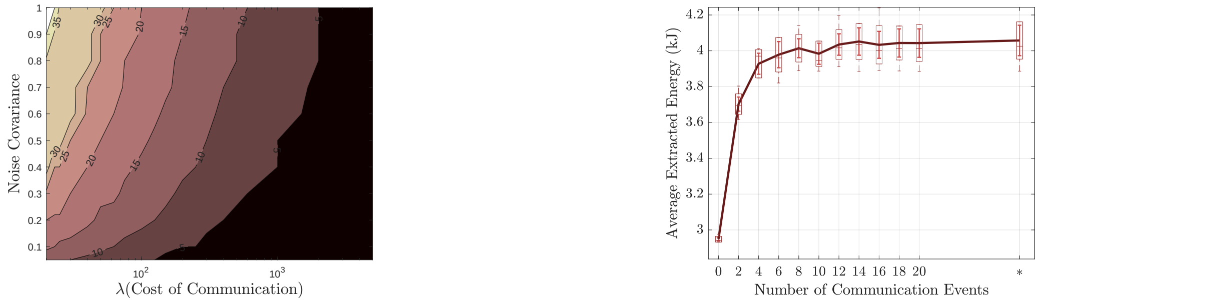
5 Results and Discussion

The objective is to maximize power extraction while minimizing control effort and communication load. Figure 2 summarizes the key performance metrics:

- **Energy Extraction:** Cumulative energy plots (Figs. 2a–2c) show that perfect-state feedback achieves the highest power capture. Event-triggered control performs nearly as well, particularly for WEC 2. Notably, the event-triggered strategy captures approximately 98% of the energy achieved by continuous communication, demonstrating high efficiency with reduced communication. Prediction-based control yields slightly lower energy, especially for WEC 1, reflecting the impact of limited feedback on coordination.
- **Communication Schedule:** As shown in Fig. 2i, the event-triggered scheme significantly reduces communication by transmitting only when necessary. These sparse transmission times result from solving an optimization problem (Eq. (16)), which optimally trades off control quality and communication cost.
- **Instantaneous Power:** Power profiles (Figs. 2d–2f) indicate effective wave synchronization under all strategies. Prediction based control shows slightly reduced peaks, especially for WEC 1. Event-triggered control retains peak alignment with the perfect state benchmark.
- **Control Inputs:** Control trajectories (Figs. 2g–2h) under event-triggered control nearly overlap with those from perfect state feedback. In contrast, the prediction-only control shows modest deviations, highlighting the benefit of even infrequent feedback updates.

Summary: Event-triggered control offers the best compromise between performance and communication cost. It achieves near-optimal energy capture and actuation quality with substantially fewer transmissions, making it well suited for bandwidth-constrained offshore environments.

Power-Communication Trade-off: Fig. 3(a) and Fig. 3(b) illustrate the trade-off between communication frequency and power extraction in a two-WEC system under event-triggered control. Fig. 3(a) is generated deterministically and shows that increasing communication cost λ or reducing noise covariance leads to fewer communication events, reflecting resource



(a) Number of total communication as the cost of communication λ and noise covariance are varied.

(b) Average extracted power vs. number of communication events (* means continuous communication)

Figure 3: Trade-off between communication cost, estimation accuracy, and energy extraction performance.

conservation. In contrast, Fig. 3(b) presents average extracted power over Monte Carlo runs with different random seeds, capturing the impact of stochastic disturbances. Power improves with more communication but plateaus, indicating diminishing returns. These results underscore the need to balance communication and energy performance in constrained marine settings.

Conclusion

This paper presents a discrete-time LQR-based control framework for a two-WEC array, jointly optimizing control inputs and communication schedules through an event-triggered strategy. The proposed approach effectively balances energy extraction performance with communication cost by enabling feedback transmissions only when necessary. Simulation results show that the event-triggered controller captures over 98% of the energy achieved by continuous communication while substantially reducing communication frequency. These results highlight the potential of communication-aware control in enabling scalable, efficient, and cost-effective operation of WEC arrays. Although we considered two WECs, the theory and the analysis extend straightforwardly to an n-WEC system. Future work will extend this framework to larger arrays with varying configurations.

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