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Deep Learning-Driven Control Optimization for Wave Energy Converters via Real-time Sea State Prediction

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Abstract

Due to the stochastic and highly dynamic nature of the ocean, wave energy converters (WECs) require sophisticated control strategies capable of adapting to changing sea states. Traditional control methods have shown promise but may rely on real-time knowledge of the incoming wave profile which is challenging. To address this, we propose a novel data-driven framework that eliminates the need for direct wave elevation measurements. Our method employs a deep neural network to predict incoming wave spectra using only physical measurements from the WEC device itself. Based on the wave spectra, a linear controller is designed for maximum power capture and using the PI controller gains, a model predictive controller (MPC) is tuned. By treating wave peak period, T_p as a continuous variable with fine resolution, our model achieves high-fidelity wave characterization without the need for external wave sensors. Simulation results show that this approach is both accurate and robust, and it holds significant promise for enabling real-time, sensor-independent WEC control in dynamic sea environments.

Keywords: Wave energy converter; LSTM; Time-frequency analysis; MPC control, PID.

1. Introduction

The global transition to renewable energy is increasingly focused on diverse sources of clean power generation. Among these, ocean wave energy stands out due to its high energy density, predictability, and abundant availability. It is estimated that the total global wave energy resource exceeds 32,000 TWh/year [1], making it one of the most promising sources of sustainable energy. Wave energy converters (WECs) are devices specifically engineered to harness the kinetic energy of ocean waves and convert it into usable electrical power. Despite their immense potential, the commercial viability of WECs remains limited by a central challenge: achieving efficient and reliable energy capture in highly variable and uncertain ocean conditions.

A WEC's ability to extract power efficiently depends critically on how well it is controlled. In practice, the hydrodynamic forces acting on the WEC fluctuate rapidly, and optimal control strategies must respond dynamically to these variations. As a result, the field has explored a wide range of control methods, including passive control (e.g., reactive and latching control) [2], model predictive control (MPC) [3], and reinforcement learning (RL) [4]. Passive control methods are simple to implement but do not adapt well to changes in sea state. MPC, while more adaptive and

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powerful, requires real-time prediction of wave excitation forces and accurate modeling of WEC dynamics. RL-based approaches offer a data-driven alternative by learning control policies from simulation, but they face sample inefficiency and generalization challenges in real environments.

A key limitation that unites all these control techniques is their reliance on wave elevation signals, either from direct sensors such as wave buoys or from model-based estimations. However, obtaining accurate real-time wave measurements in offshore environments is inherently difficult. Ocean dynamics are nonlinear, nonstationary, and subject to external disturbances like tides, storms, and turbulence. Furthermore, wave sensors are expensive, prone to damage, and introduce latency and communication delays [5]. This dependence on wave profile information severely constrains the scalability and robustness of advanced control systems in real-world deployments [6].

To address this issue, we propose a sensor-independent, data-driven control framework that leverages only internal WEC measurements (e.g. heave position, velocity, and power take-off (PTO) force) to estimate sea state and tune the controller. These internal signals are inherently available onboard and contain information about the incident wave dynamics. We employ a long short-term memory (LSTM) neural network trained on time-frequency representations of WEC responses to predict T_p as a continuous variable with high resolution. The peak wave period (T_p) is defined as the period corresponding to the maximum energy in the wave spectrum. It characterizes the dominant frequency of incoming ocean waves and is a key parameter in determining the optimal control strategy for WECs. To enhance model robustness and generalizability, additive Gaussian white noise is introduced during the data generation phase. Furthermore, excitation forces are generated for T_p values sampled at 0.01 s intervals, and features are extracted using a 50-second sliding time window to ensure that the LSTM model captures all relevant temporal and spectral characteristics of the system response. Once T_p is estimated, a proportional-integral (PI) controller is tuned using precomputed optimal gains corresponding to the identified sea state. To handle physical constraints and improve robustness, the PI controller is further extended into an MPC framework. Using a linear matrix inequality (LMI)-based method, we tune the MPC weight matrices such that its behavior matches the PI controller in unconstrained scenarios, while enforcing constraint satisfaction when limits are active [7].

This paper presents a novel control pipeline that combines LSTM-based sea state prediction with PI-tuned MPC to maximize WEC energy capture. The proposed framework removes the dependency on external wave sensors, adapts to changing conditions in real time, and ensures constraint-aware control—offering a scalable and deployable solution for future ocean energy systems.

2. Methodology

To enable real-time WEC control without relying on external wave measurements, we propose a sensor-independent framework that predicts the T_p using only internal WEC signals: position (z), velocity ($\dot{z}$), and PTO force (F_{PTO}). A comprehensive dataset is generated using the JONSWAP wave spectrum with varying T_p values from 1 to 5 s, and the resulting signals (z, $\dot{z}$, F_{PTO}) are sampled at 100 Hz for a duration of 400 seconds.

To effectively capture the non-stationary and multi-frequency nature of the WEC response, we transform the raw time-domain signals into the time-frequency domain using short-time Fourier transform (STFT) and continuous wavelet transform (CWT) [8,9]. This dual representation preserves both local frequency variations and global temporal structure, providing a rich and informative feature space for learning. Figure 1 illustrates the importance of using time-frequency representations instead of time domain or frequency domain only. While time-domain signals and power spectral density (PSD) curves provide some indication of wave characteristics, they lack temporal resolution or fail to reveal dynamic spectral changes. Even with a 1 s change in T_p values, the time domain and frequency domain signals cannot differentiate the effect. In contrast, STFT and CWT representations clearly differentiate between wave periods by showing how spectral energy varies over time enabling fine-grained wave parameter estimation.

The combined STFT and CWT features are used to train a LSTM neural network to predict T_p as a continuous regression target. Several features are extracted from the WEC response, however, best 20 features with high importance score are selected for the neural network modeling. For this particular task, LSTM is chosen for its proven capability to learn long-term temporal dependencies and capture the sequential structure inherent in WEC dynamics [10]. Once T_p is predicted, corresponding optimal PI controller gains (K_p and K_i) are determined that maximize power capture. A detailed control approach is presented in the next section.

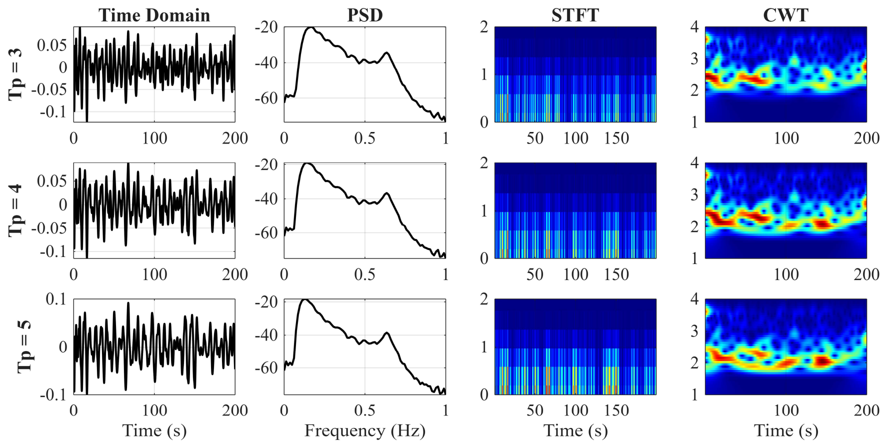


Fig. 1. WEC physical measurement representation for different T_p. Column 1: Time domain, Column 2: Power Spectral Density, Column 3: Short-time Fourier Transform, Column 4: Continuous Wavelet Transform. Row 1: $T_p = 3$ s, Row 2: $T_p = 4\ s$, Row 3: $T_p = 5\ s$.

3. Control Design

3.1. Liner Control: PI

For a heaving point absorber WEC, the equation of motion can be simplified as:

$$m\ddot{z}(t) + b\dot{z}(t) + kz(t) = F_{\text{exc}}(t) - F_{\text{PTO}}(t) \tag{1}$$

Where, $z(t)$ is the vertical position of the buoy, $F_{\text{exec}}(t)$ is the wave excitation force, $F_{\text{PTO}}(t)$ is the Power Take-Off force, and m, b, and k are the mass, damping, and hydrostatic stiffness, respectively [11]. The PI controller used to maximize energy capture is expressed as:

$$F_{\text{PTO}}(t) = K_p\dot{z}(t) + K_i z(t) \tag{2}$$

The control gains K_p and K_i are tuned such that the controller impedance matches the hydrodynamic radiation impedance of the WEC under a given wave condition (i.e., specific T_p). This impedance-matching ensures phase alignment between the velocity $\dot{z}(t)$ and excitation force $F_{\text{exec}}(t)$, maximizing power absorbed:

$$P_{avg} = \lim_{T\to\infty} \frac{1}{T}\int_0^T F_{PTO}(t) \cdot \dot{z}(t)dt \tag{3}$$

Optimal K_p and K_i values are computed offline for a range of T_p, and later used as inputs to guide the design of an equivalent MPC controller.

3.2. PI-tuned MPC

To incorporate physical constraints and enhance control robustness, we adopt an MPC framework that mimics the behavior of the PI controller in the unconstrained case, while safely handling state and input constraints when active.

The classical MPC optimization problem is:

$$\mathcal{V}(x(k), u(k)) = \min_{u(k)} x'(N \mid k)\mathrm{P}x(N \mid k) + \sum_{i=0}^{N-1} x'(i \mid k)\mathrm{Q}x(i \mid k) + u'(i \mid k)\mathrm{R}u(i \mid k) \tag{4}$$

where the notation' denotes the transpose of a vector, such that

$$x(i+1 \mid k) = \mathrm{A}x(i \mid k) + \mathrm{B}u(i \mid k), i = 0, \ldots, N-1 \tag{5}$$

The weight matrices Q, R, P can be optimized using the following optimization problem. A more detailed formulation can be found in [12].

$$
\begin{aligned}
\min_{\mathcal{K},Q,R,P} \quad & J(\mathcal{K},Q,R,P) \\
\text{s.t.} \quad & Q \geq 0, P \geq 0, R \geq \sigma I \\
& (\mathcal{R} + \mathcal{S}'Q\mathcal{S})\mathcal{K} + \mathcal{S}'Q\mathcal{T} = 0 \\
& \kappa_0 = K
\end{aligned}
\tag{6}
$$

We aim to choose weight matrices Q, R, and terminal weight P such that the unconstrained MPC replicates the PI controller behavior. This leads to the following LMI-based optimization problem. Given a desired feedback gain K, there exist MPC cost matrices Q, R, P such that the unconstrained MPC satisfies:

$$u_0 = -Kx_0 = \arg\min_u \sum_{i=0}^{N-1} (x_i^\top Q x_i + u_i^\top R u_i) \tag{7}$$

The resulting optimization yields cost matrices that ensure the MPC inherits the small-signal behavior of the PI controller, enforces constraint satisfaction during large transients, and guarantees global asymptotic stability when appropriate terminal sets and costs are used. This hybrid controller effectively combines the simplicity of PI control with the robustness of MPC, enabling reliable operation under both nominal and disturbed sea conditions.

4. Results and Analysis

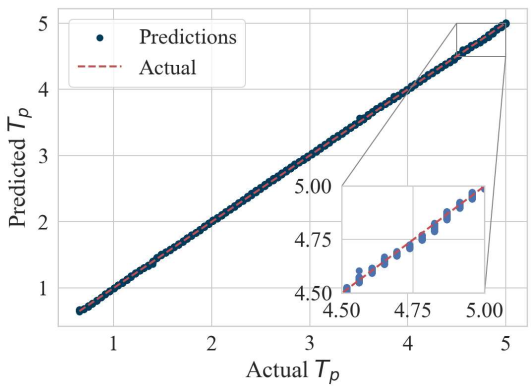
The LSTM model demonstrates high accuracy in predicting the peak wave period T_p from WEC response signals transformed into the time-frequency domain. A list of optimal LSTM model parameters is shown in Table 1. The model was trained on a Python 3.12 with TensorFlow 2.19.0.

Table 1. LSTM Hyperparameters.

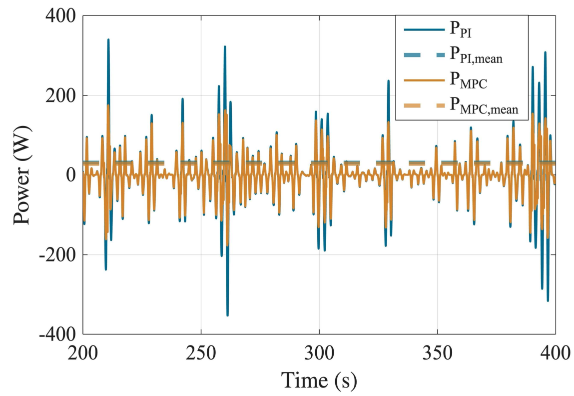
Hyperparameter	Value / Range	Description
Input features	3	Position, velocity, PTO force
Number of LSTM layers	2	Stacked layers for deeper temporal modeling
Hidden units per layer	64	Size of LSTM hidden state
Dropout rate	0.2	Dropout applied between LSTM layers
Output dimension	1	Scalar T_p value
Loss function	Mean Squared Error (MSE)	Penalizes large prediction errors
Optimizer	Adam	Adaptive learning rate optimizer
Learning rate	0.001	Tuned using grid search
Batch size	32	Number of sequences per training batch
Number of epochs	100 (with early stopping)	Maximum epochs for training
Early stopping patience	10	Stops training if no validation improvement for 10 epochs

Figure 2(a) shows a scatter plot comparing the predicted T_p values against the true labels for a test dataset covering a continuous range of $T_p = 1$ to 5 s. The predicted values (blue dots) closely align with the identity line (red dashed), indicating excellent model fit across the entire range. A zoomed-in inset highlights the model's fine resolution and its ability to distinguish small variations in wave period (e.g., from 4.50 to 5.00 s). This confirms that the use of STFT and CWT features, enables precise and continuous sea state estimation without requiring direct wave measurements.

Using the predicted T_p, optimal PI controller gains (K_p, K_i) are selected from an offline-optimized database. These gains are also used to tune an MPC via LMI-based matching to ensure similar dynamic behavior when constraints are inactive. Figure 2(b) presents the resulting power outputs from the WEC under both PI and MPC control strategies over a 200-second simulation interval. The instantaneous power outputs P_{PI} and P_{MPC} are plotted along with their respective mean values ($P_{PI,mean}$ and $P_{MPC,mean}$). As shown, both controllers yield comparable mean power capture with $P_{PI,mean} = 31.61$ W and $P_{MPC,mean} = 30.46$ W. MPC achieves a bit lower average power compared to the PI controller since PI is optimally tuned for the maximum power capture and MPC is trying to match its DC gain with the PI gains. In this context, the DC gain refers to the steady-state gain of the unconstrained MPC—how the output responds to constant or slowly varying inputs once transients have settled. By aligning this DC gain with that of the PI controller, the MPC can emulate the PI's steady-state performance when constraints are inactive. However, due to the approximate nature of the LMI-based tuning process and solver limitations, the MPC's DC gain does not always perfectly replicate the PI controller's response. This results in a slight mismatch in both instantaneous and average power outputs. Nevertheless, the MPC exhibits smoother control actions and fewer high-magnitude transients,



(a)



(b)

Fig. 2. (a) LSTM model prediction. (b) WEC response for PI and MPC controller for LSTM predicted T_p.

especially around time intervals where system dynamics change rapidly. This behavior demonstrates the MPC's ability to preserve PI performance in nominal conditions while adding robustness through constraint enforcement in practical scenarios. The reduction in power variability under MPC also implies reduced structural loading, which is advantageous for the longevity and safety of WEC devices.

5. Discussion and Future Work

By combining time-frequency analysis (via STFT and CWT) with LSTM-based regression, the model achieves high-resolution T_p predictions across a continuous range of sea states. The integration of these predictions into a PI-tuned MPC control loop provides both energy efficiency and robustness, addressing the limitations of purely linear or sensor-dependent controllers. The comparative results show that MPC tuned via LMI preserves the favorable characteristics of the PI controller while enforcing physical constraints during transients. This hybrid structure is particularly advantageous for offshore environments where wave excitation forces can vary unpredictably and where system protection is critical. The smooth power output of the MPC also implies lower mechanical stress on WEC components, which can translate to improved device longevity and reduced maintenance. While promising, the approach is currently limited to simulated data and single-parameter prediction. Future work will extend the model to estimate additional wave parameters (e.g., wave height), incorporate online PI-MPC tuning for better adaptability, and validate the full pipeline through hardware-in-the-loop and field experiments to ensure real-world deployability. Additionally, evaluating the MPC's constraint-handling capabilities using real WEC physical limits will be an important direction for ensuring safe and reliable deployment.

6. Conclusion

This work proposed a sensor-independent, data-driven control framework for Wave Energy Converters that predicts the peak wave period (T_p) using an LSTM model trained on time-frequency features derived from position, velocity, and PTO force measurements. The predicted T_p is used to determine optimal PI controller gains, which are then employed to tune an MPC via a linear matrix inequality-based method. Simulation results demonstrate that the model accurately estimates T_p across a continuous range, even under noise, and that the LMI-tuned MPC achieves robust and constraint-compliant performance comparable to PI control in unconstrained scenarios. This framework eliminates the need for external wave sensors and offers a scalable solution for real-time WEC control.

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