ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING TECHNIQUES USED IN WAVE ENERGY CONVERTER SYSTEMS

TEHNICI DE INTELIGENȚĂ ARTIFICIALĂ ȘI MACHINE LEARNING FOLOSITE ÎN SISTEMELE DE CAPTARE A ENERGIEI VALURILOR

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Abstract: *This paper analyzes the integration of Artificial Intelligence (AI) and Machine Learning (ML) in Wave Energy Converter (WEC) Systems. Although the ocean energy potential is immense, the stochastic nature of waves limits their cost competitiveness (LCOE) compared to wind or solar energy. Going beyond traditional control based on linear models, ML algorithms (such as Recurrent Neural Networks or Reward Learning) allow for real-time adaptation to irregular sea conditions. The paper explores the optimization of the Power Extraction System (PTO) through these technologies, aiming to maximize the energy captured and ensure structural resilience in extreme conditions.*

Keywords: wave energy, ML algorithms, structural resilience, maximal energy captured.

Rezumat: *Această lucrare analizează integrarea Inteligenței Artificiale (AI) și a Învățării Automate (ML) în Sistemele de Captare a Energiei Valurilor (WEC). Deși potențialul energetic oceanic este imens, natura stocastică a valurilor limitează competitivitatea costurilor (LCOE) comparativ cu energia eoliană sau solară. Depășind controlul tradițional bazat pe modele liniare, algoritmii ML (precum Rețelele Neuronale Recurente sau Învățarea prin*

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Recompensă) permit adaptarea în timp real la condițiile neregulate ale mării. Lucrarea explorează optimizarea Sistemului de Extracție a Puterii (PTO) prin aceste tehnologii, vizând maximizarea energiei captate și asigurarea rezilienței structurale în condiții extreme.

Cuvinte cheie: energia valurilor, algoritmi de ML, rezilienta stucturii, energie maxima captata.

1. Introduction

The complexity of the marine environment and the limits of classical methods.

Wave energy is considered one of the most difficult renewable resources to exploit due to the complex interaction between fluid and structure. Unlike wind, where air flow is relatively predictable, ocean waves exhibit high nonlinearity [1]. Traditionally, marine engineering has used Proportional-Integral-Derivative (PID) control methods. Although robust, these systems “look” backward: they react to the already produced movement of the device. To achieve maximum efficiency, we need Model Predictive Control (MPC), which can “anticipate” the force of the next wave. This is where AI comes in, transforming a reactive system into a proactive one. Basically, the transition to this type of control is not just an incremental improvement, but a paradigm shift: the device no longer “fights” against the wave, but cooperates with it, anticipating its movement like an experienced surfer.

The research objective is the transition to "Smart WEC". The objective of this study is to demonstrate that digitalization through ML (Machine Learning) is not just an accessory, but a necessity for the survival of the marine energy industry [1]. We focus on three fundamental pillars:

I. Forecasting: Knowing the sea state 10-30 seconds in advance.
II. Optimization: Adjusting the mechanical parameters of the device to resonate with the incident wave.
III. Survivability: Identifying critical waves that can destroy the structure.

Figure 1 illustrates the data flow in such an intelligent system, according to the hierarchical control architectures analyzed in recent literature [2].
Existing synthesis studies in the literature often focus on isolated aspects of marine engineering, such as hydrodynamics or isolated control mechanisms.

The novelty of this work lies in the aggregation of ML (Machine Learning) and AI (Artificial Intelligence) applications across the entire operational spectrum of WEC (Wave Energy Converter) systems. By interconnecting real-time wave forecasting (LSTM), proactive control of PTO systems (RL) and predictive maintenance (CNNs) in a unified "Smart WEC" framework, this article provides a holistic perspective on digitalization in the field of ocean energy.

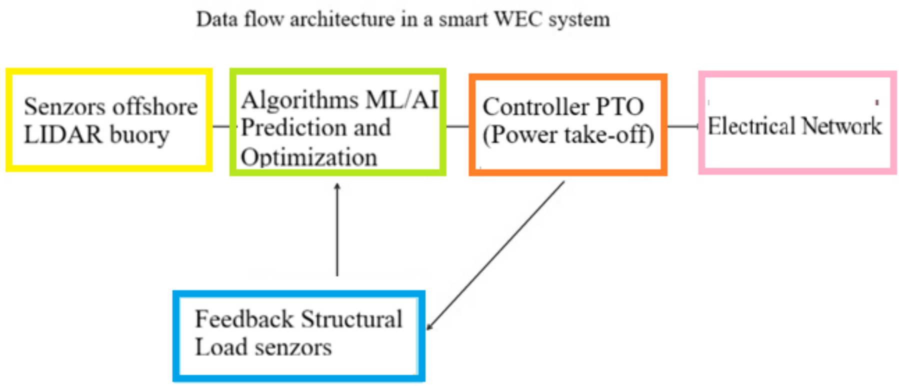

Fig 1. Data Flow Architecture in a Smart WEC System. (Original illustration generated by the authors, adapted from the intelligent systems architecture described by Zhang et al. [2])

2. ML techniques for energy resource prediction

a. The importance of time horizons in prediction

In wave energy converter (WEC) systems, the success of control depends on the algorithm's ability to predict the excitation force with a time horizon of 10 to 30 seconds. This window is crucial to allow the Power Extraction System (PTO) to modify its damping parameters [3]. From an engineering perspective, this 10-30 second time frame is not chosen randomly. It represents a critical trade-off between the mechanical inertia of the system (which requires physical time to actuate hydraulic valves or electric motors) and the ocean's "horizon of chaos," where mathematical accuracy decreases exponentially with each second added to the prediction.

Classical statistical methods tend to fail in rough sea conditions. For this reason, current research has focused on Long Short-Term Memory (LSTM) neural networks. These are a variant of Recurrent Neural Networks

(RNN), being able to "learn" long-term dependencies from sequential sensor data [3].

b. Applying LSTM models in time series analysis

An LSTM model processes data from surface buoys or submerged pressure sensors. The major advantage is the ability to filter out “noise” and identify the pattern of energy-carrying waves. According to recent studies, using LSTM (Long Short Term Memory) architecture can reduce the prediction error (RMSE) by up to 25% compared to traditional methods under irregular sea state conditions, specifically when testing with non-linear wave spectra like JONSWAP [3][4]. In essence, we can think of this LSTM network as a form of “digital intuition”. Like an experienced sailor who “feels” the basic rhythm of the sea beyond the noise of small surface waves, the algorithm learns to ignore high-frequency turbulence (energetically irrelevant) and focus exclusively on the swell that carries usable energy.

The graph in Figure 2 shows the performance of AI Prediction (Actual vs. Predict). Below we have regenerated the graph comparing the actual wave height with the prediction made by an LSTM model over a time horizon of 20 seconds.

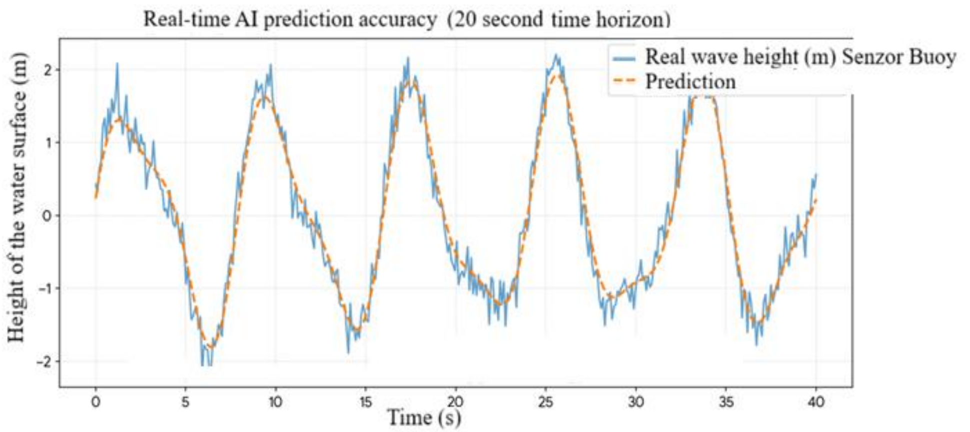

Fig 2. Real-time AI Prediction Accuracy (Time Horizon: 20s). Comparison between the real wave and the prediction generated by the neural network. (Source: Original graph generated by the authors, based on the comparative methodology of Bento et al. [4])

3. Real-time control optimization (Reinforcement Learning)

The Concept of Agent and Reward in the Context of WEC

If in the previous paragraph we used neural networks to predict the future, in actual control we need a system that learns from mistakes and successes. Reinforcement Learning (RL) uses an “Agent” that interacts with the “Environment” (the ocean and the turbine structure) [5].

Unlike classical methods, the RL Agent does not need a perfect mathematical mapping of the system. It receives a reward (the instantaneous electrical power extracted) and its goal is to maximize this reward in the long term, adjusting the PTO (Power Take Off) resistance force in milliseconds. [5]. The agent learns from the interaction with the ocean.

The Actor-Critic algorithms for continuous control

In wave energy, we need fine and continuous adjustments. Algorithms such as Proximal Policy Optimization (PPO) or Deep Deterministic Policy Gradient (DDPG) are the current standard [5]. They work through a dual structure:

- The Actor: Proposes an adjustment to the damping coefficient or stiffness of the structure.
- The Critic: Evaluates whether that adjustment has resulted in a real increase in power or whether it has expose to risk the integrity of the turbine.

To highlight why this technology is superior to traditional methods, we have summarized the main differences between control strategies in table 1. Although PID controllers offer high reliability due to their simplicity, they are unable to adapt to the nonlinear hydrodynamics of ocean waves. In contrast, classical MPC control offers excellent predictive capabilities but is often limited by prohibitive real-time computational costs. RL overcomes this shortcoming by shifting the computational burden to the offline training phase, thus enabling adaptive and near-instantaneous control during operation.

From this comparison it is clear that although the initial computational cost for training RL models is higher, the long-term operational benefit justifies the investment. The flexibility of the algorithms to learn directly from the data eliminates the need for constant manual recalibration, typical of classical PID methods.

Table 1. **Comparative analysis of control methods for WEC**

Feature	Linear Control (PID)	Predictive Control (MPC)	Reward Learning (RL)
Model Complexity	Low (Simple model)	High (Requires exact mathematical model)	Adaptive (Learns directly from data)
Prediction Capacity	Non-existent (Reactive)	Excellent (computationally expensive)	Excellent (Real-time)
Nonlinearity Handling	Weak	Good	Very good
Computational Resources	Minimum	Very large	Averages (after the model is trained)
Technology Source	Industrial Standard (1970+)	Engineering Standard (2000+)	Frontier of Research (2020+)

Maximizing the power output

The efficiency of an RL (Reinforcement Learning) algorithm is measured by its ability to maintain the system in resonance. The absorbed power is defined by the relation (1) [5]:

$$P(t) = F_{pto}(t) \cdot v(t) \qquad (1)$$

where:

P(t) - is the instantaneous power
$F_{pto}(t)$ – is the force exerted by the control system
v(t) - is the oscillation speed of the floating body.

The RL algorithm modifies the force exerted by the control system, so that the speed *v(t)* is always in phase with the wave excitation force, which can lead to efficiency improvements of up to 20% in variable wave climates compared to passive damping strategies.

4. Predictive maintenance and fault detection

It is very important to move from reactive to **proactive** maintenance.

In the offshore environment, maintenance costs can represent up to 30-50% of the LCOE (Levelized Cost of Energy). AI-based Fault Detection and Isolation (FDI) systems monitor the turbine's "vital signs" and can identify an anomaly weeks before a part fails, techniques validated for diagnosing WEC systems [6][7].

Convolutional Neural Networks (CNN) are used in structural analysis.

A CNN algorithm can distinguish between normal sea noise and the specific vibration of a worn bearing. A complementary tool is the Autoencoder (AE), which learns correct operation and generates an Anomaly Score when deviations occur [6].

AI helps maintain the reliability function (2) at a high level by minimizing the failure rate [6]:

$$R(t) = \exp\left(-\int_0^t \lambda(t)dt\right) \qquad (2)$$

where:

R(t) - the probability that the system will operate without failure until time t

λ(t) - is the Failure Rate, which the AI tries to keep to a minimum through early prediction

In Figure 3 is the graph of predictive maintenance, with the frequency of anomalies in time or cycles of operation. The aim is to reduce operational costs OPEX.

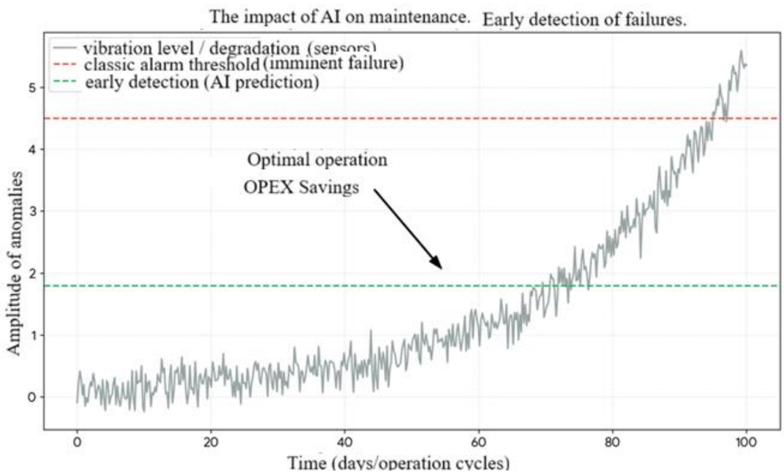

Fig.3. Impact of AI on Maintenance: Early Detection of Failures. The system identifies the deviation (green line) before reaching the critical threshold (red line). (**Source: Original conceptual graph generated by the authors, adapted from the diagnostic strategies analyzed by Papini et al. [7]**)

5. Hydrodynamic modeling through surrogate models

CFD (Computational Fluid Dynamics) simulations are extremely expensive, taking days on a supercomputer, which does not allow for rapid design optimization [8].

AI-based surrogate models operate as a "black box" trained on CFD (Computational Fluid Dynamics) data. Once trained, the model can predict the hydrodynamic response in fractions of a second [8]. Techniques include Gaussian Processes (Kriging) and Physics-Informed Neural Networks (PINNs), which obey the laws of energy conservation.

Artificial Intelligence, ML and deep learning techniques for controlling and optimizing WEC systems are also analyzed in [9], [10]. The field is a real challenge and generates multiple perspectives.

Table 2 illustrates the efficiency of the computing models. This drastic reduction in computational time opens the possibility of testing thousands of geometric scenarios in a single day, something impossible with conventional methods. Thus, AI becomes not just an operating tool, but a catalyst in the early design phase, allowing engineers to innovate rapidly without time constraints.

Table 2. **Comparison of hydrodynamic modeling methods**

Computational method	**Time estimated / simulation**	**Relative accuracy**	**Hardware requests**
CFD (Navier-Stokes)	12 - 48 hours	99% (References)	Cluster HPC
Potential Models (Linear)	10 - 30 minutes	80 - 85%	Workstation
Surrogate Model (AI)	< 0.1 seconds	95 - 98%	Laptop Standard

The approximation achieved by AI can be expressed in a simplified way by the relationship (3), where the model tries to minimize the residuals relative to physical reality.

$$y = f_{hat}(x) + \varepsilon \tag{3}$$

where:

y - the estimated hydrodynamic result (e.g. impact force),

$f_{hat}(x)$ - the approximation function generated by the neural network,
ε - the systematic modeling error.

6. Case study and real industrial applications

CorPower from Wave Spring technology is used to optimize by phase control and uses RL algorithms to adjust the pressure in the prestressing system, adapting to irregular waves faster than linear control [5].

Structural Protection can be made with **WaveRoller** device, LSTM networks predict extreme loads, giving the system the necessary time (5-10 seconds) to enter a safe position (Safe Mode) [2].

The efficiency of AI optimization is measured by the Capture Width Ratio (**CWR**) indicator, which indicates how much of the energy available in the wavefront is effectively converted into electricity, calculated with equation (4):

$$CWR = \frac{P_{extracted}}{P_{wave} \cdot D} \tag{4}$$

where:

$P_{extracted}$ - the average electrical power produced (optimized by the AI agent),
P_{wave} - the incident wave energy flux per meter of wavefront,
D - the characteristic dimension (width) of the device.

7. Structural resilience in extreme conditions

This chapter discusses the role of AI in protecting the physical integrity of WEC systems. It is important to emphasize that no amount of production optimization is economically worthwhile if the equipment cannot survive the first major storm. Therefore, we consider the AI-assisted survivability function as the digital “insurance policy” of the entire investment.

It is as follows:

• Critical wave detection: LSTM algorithms identify rogue wave patterns 10-15 seconds before impact [1].

• Survival strategies: Activating submersion or locking the PTO to prevent exceeding mechanical limits [1].

• Damping adjustment: Through RL, the system modifies stiffness to dissipate excess energy [5].

The impact force on the structure is calculated with the relation (5). The AI refines the hydrodynamic coefficients to estimate the impact force [1]:

$$F_{impact} = \frac{\rho}{2} c_s \cdot A \cdot v^2 \quad (5)$$

where:

ρ - the seawater density
c_s - the structural impact coefficient adjusted by AI
A – the exposed surface area
v – the relative wavefront velocity

Challenges and limitations of AI/ML methods in WEC systems

Despite the significant advantages outlined above, the implementation of AI and ML in marine energy faces several critical limitations that need to be addressed before large-scale commercialization. First, deep learning models require massive amounts of high-quality training data. In the offshore sector, collecting reliable data from sensors over the long term is recognized as challenging due to their degradation in highly corrosive saltwater environments.

Second, algorithms such as Deep Reinforcement Learning involve high computational cost. Running complex neural networks requires robust hardware, which increases power consumption and raises cooling issues inside the sealed enclosure of an offshore WEC. Furthermore, generalization capability remains a critical obstacle. An RL agent trained on North Sea wave spectra could perform poorly if deployed in the Mediterranean Sea without extensive retraining.

Finally, the transition to "Smart WECs" introduces cybersecurity risks. As offshore farms become increasingly dependent on cloud computing and remote-control adjustments, they become vulnerable to cyberattacks that could manipulate PTO settings and cause physical damage to the infrastructure.

8. Conclusions

The paper analyses the integration of Artificial Intelligence (AI) and Machine Learning (ML) in Wave Energy Converter (WEC) Systems. The integration of Artificial Intelligence and Machine Learning techniques represents a decisive step towards the technological maturity of the wave energy sector.

First, control optimization through **Reinforcement Learning** allows an increase in energy capture efficiency by up to 20% compared to traditional methods. This real-time adaptation capacity is essential for maximizing annual yield.

Second, economic viability is improved by lowering LCOE. **Surrogate models** reduce design time from months to seconds, and predictive maintenance reduces operational costs by early identification of defects.

Finally, the resilience of structures depends on the prediction of extreme loads. **LSTM** (Long-Short Time Memory) networks provide the necessary time window to activate survival modes, protecting assets against destruction.

The field of AI techniques and ML methods is a real challenge and generates multiple perspectives in the field or wave energy converters.

Looking ahead, future research directions should focus on developing high-precision Digital Twins for entire wave energy converter systems, integrating Physics Informed Neural Networks (PINNs) to ensure that ML models respect the fundamental laws of hydrodynamics. Addressing the cybersecurity framework for offshore energy networks will also be a vital area of study to ensure secure and continuous energy production.

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