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EVALUATING THE PERFORMANCE OF LONG SHORT-TERM MEMORY ALGORITHM IN LATCHING CONTROL FOR NON-BUOYANT WAVE ENERGY CONVERTERS

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Abstract

In recent years, there has been a surge in research aimed at harnessing the energy of ocean waves for effective utilization. Among the various types of wave energy converters (WECs), point absorber WECs have emerged as a preferred choice due to their enhanced efficiency when equipped with an appropriate control mechanism. To achieve this, an efficient control strategy known as the latching control has been employed. The latching control mechanism is designed to halt the device's motion at its maximum amplitude, specifically when the velocity reaches zero. Concurrently, this control strategy permits the device to resume its motion when the wave conditions are optimal for maximum energy extraction. The duration of the holding time for the WEC is of paramount importance in maximizing energy extraction. In this study, a recurrent neural network (RNN), specifically the Long Short-Term Memory (LSTM) algorithm, was trained using data collected from an experimental campaign and to predict the latching time for various wave conditions, thereby enhancing the efficiency of energy extraction from point absorber WECs.

Kew words: Wave Energy Converter. Latching control, Recurrent neural network

Introduction

The potential of fossil fuels to meet future energy demands is constrained by the severe impacts of global warming and climate change. The International Energy Agency has issued a warning, indicating that energy-related greenhouse gas (GHG) emissions are poised to result in significant climate degradation, potentially leading to an average global warming of 6 degrees Celsius [1]. Reducing harmful impacts on nature and the financial system is necessary when tackling these problems to ensure a brighter and improved energy future for people [2]. Renewable energy sources are poised to become the primary energy source for the future. Lately, numerous experts and scientists have suggested various methods to harness renewable energy from natural elements like water, wind, sun, geothermal, and organic matter [3]. However, the development of large-scale, comprehensive renewable energy systems is still in its infancy, particularly in terms of smart control management [4]. To address this challenge, Artificial Intelligence (AI) has been integrated into renewable energy systems to provide smart control and decision-making capabilities. In essence, AI emulates human intelligence with a broad spectrum of skills including reasoning, identifying patterns, learning from experiences, and extracting insights from data [5]. AI has emerged as a pivotal force in the renewable energy field, being applied to improve various aspects of power generation [6]. For instance, AI is utilized in optimizing energy output through predictive maintenance, where AI algorithms analyze sensor data from wind turbines, solar panels, and other devices to forecast maintenance requirements, thereby preventing unforeseen breakdowns and prolonging the equipment's lifespan. In the realm of energy forecasting, machine learning algorithms predict energy generation based on weather patterns, historical data, and other factors, aiding grid operators in managing supply and adjusting operations as needed. Furthermore, AI is employed in the continuous monitoring of renewable energy systems, identifying inefficiencies and proposing enhancements to boost energy efficiency.

AI plays a crucial part in refining grid management, where it aids in controlling energy consumption by forecasting peak demand periods and modifies energy production from green sources as needed. This guarantees a consistent flow of energy and decreases the reliance on oil and gas for back-up power. Additionally, AI programs help in maintaining equilibrium between supply and demand on an instantaneous basis, facilitating the incorporation of variable, renewable energy sources like solar and wind into the grid without jeopardizing its stability. To enhance energy efficiency, AI optimizes energy storage methods, such as batteries, by predicting the ideal times for energy collection and discharge. This boosts the effectiveness of renewable energy systems and ensures a continuous supply of energy. Moreover, AI scrutinizes the energy usage habits of both residential and commercial areas, recommending strategies to lower energy consumption and incorporate more green sources. In the realm of renewable energy research and development, AI hastens the search for new materials for more effective solar panels and windmills by sifting through extensive datasets to spot promising candidates. AI tools help in the simulation and optimization of renewable energy systems, leading to advancements in the design of turbine blades, configurations of solar panels, and other components. Regarding market analysis, AI aids in the examination of trends and behaviors in the market, guiding investment and policy choices in the renewable energy field. AI models support the development of intelligent grids capable of smoothly integrating substantial amounts of renewable energy, enhancing reliability and lowering expenses. In the field of Data Analytics, AI deals with huge quantities of data from renewable energy sources to uncover insights on performance, usage patterns, and areas for enhancement. Furthermore, in the area of risk evaluation, AI assesses the potential dangers of renewable energy projects, encompassing financial, environmental, and operational hazards, to facilitate well-informed decisions.

In this research, an effective control technique, known as the latching control, has been employed to augment the efficiency of non-buoyant type WEC. The latching control mechanism is engineered to cease the device's motion at its crest and trough during the cyclic wave, particularly when the velocity reaches zero. Concurrently, this control strategy enables the device to initiate motion again when the wave conditions are conducive to optimal energy extraction. The duration of the holding time for the WEC is crucial for maximizing energy extraction. In this study, a recurrent neural network (RNN), specifically the Long Short-Term Memory (LSTM) algorithm, was trained utilizing data gathered from an experimental campaign. The objective was to predict the latching time for various wave conditions, thereby improving the efficiency of energy extraction from point absorber WECs.

Latching Control

Latching control is a technique that halts the motion of a device at its extreme positions, i.e., when its velocity reaches zero, and releases the device when the wave is in a favourable phase, allowing for maximum energy extraction [7].

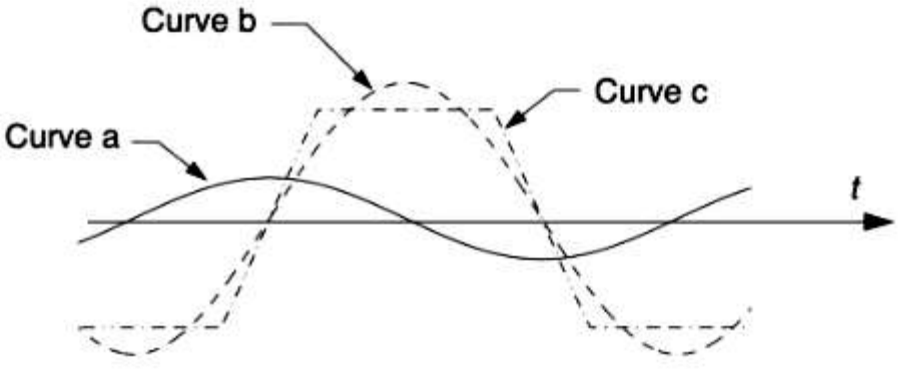


Figure 1 Latching control [7]

In Figure 1, curve (a) represents the incident wave elevation, while curve (b) shows the buoy's movement, which remains in phase with the wave. Curve (c) illustrates the effect of latching, where the device is stalled at its extreme positions to maintain phase alignment with the incident wave. The key parameter in achieving effective latching is controlling the timing for holding and releasing the device. In regular wave conditions, the optimal latching delay can be determined as half the difference between the wave period and the device's natural period. Eight different control methods are proposed by [8], with latching control being one of the most effective. Three latching control techniques studied by [9] include peak absorbed-energy matching, peak amplitude matching, and peak-velocity excitation matching, all of which show significant improvement in wave energy harvesting. A further strategy proposed by [10] employs a hydraulic power take-off (PTO) system, where de-latching occurs only when the PTO force exceeds a specific threshold, removing the need for future wave prediction. The optimal latching time, as formulated by [11], is given by:

$$T_{latch} = \frac{(T_w - T_o)}{2} \tag{1}$$

where T_w is the wave period and T_o is the resonance period of the device's heave motion. The corresponding unlatching time is:

$$T_{unlatch} = T_w - 2T_{latch} = T_0 \tag{2}$$

The implementation of latching control significantly augments the efficiency of wave energy conversion by optimizing phase control, accelerating the motion, and elevating the amplitude of excitation. An approach that has been proposed for simplification by [11] involves determining the latching time based on the period of the wave, rather than depending on forecasts of future wave conditions. This strategy mitigates the technical complexities associated with the implementation of latching control. However, in scenarios where the future conditions of waves can be reliably forecasted, such as in environments characterized by regular or semi-predictable wave climates, a control strategy based on predictions may offer greater precision in energy extraction. This is because such a strategy could align the device's motion more closely with the forthcoming waves, thereby optimizing the process of energy extraction. The use of prediction-based control could be particularly beneficial in situations of irregular sea conditions, where real-time conditions of the waves may not fully encapsulate the intricate dynamics of the incoming waves. In such instances, predictions could assist in anticipating the patterns of the waves, thereby enabling adjustments to the latching time for enhanced performance.

LSTM Algorithm

LSTM networks are a specialized form of RNN designed to address the challenge of vanishing gradients during training. By employing a series of gates, LSTMs enable the learning of long-term dependencies, making them highly effective in analyzing sequential data such as time series, text, and speech. The architecture's ability to manage information flow through gates and a memory cell distinguishes it from traditional RNNs by mitigating the gradient vanishing problem. As a result, LSTMs have been widely adopted in applications such as natural language processing, speech recognition, and time series forecasting.

The core of the LSTM architecture is composed of three gates: the input gate, forget gate, and output gate. These gates regulate the flow of information using sigmoid functions, which produce outputs between 0 and 1. The forget gate controls how much of the previous cell state C_{t-1} is retained by the current cell. It operates by applying a sigmoid function to the hidden state from the previous time step $h_{t-1}$and the current input x_t, generating a forget factor f_t:

$$f_t = \sigma\left(W_f.[h_{t-1}, x_t] + b_f\right) \tag{3}$$

Here, W_f represents the weight matrix for the forget gate, b_f is the bias term, and σ is the sigmoid activation function, which maps the output to values between 0 and 1, indicating the degree to which the past information should be retained.

The input gate determines which information from the current input x_t should be added to the cell state. This involves two key components: the input gate layer, which decides which values to update, and the candidate values $\acute{C}_t$, which represent new information to be incorporated into the cell state. The input gate is defined as follows:

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (4)$$

Candidate cell state

$$\acute{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (5)$$

In these equations, W_i and W_c are the respective weight matrices, b_i and b_c are bias terms, and tanh is the hyperbolic tangent function, which outputs values between -1 and 1 to determine the new candidate values for the cell state.

The updated cell state C_t is calculated by combining the effects of the forget gate and the input gate. The forget gate determines the fraction of the previous cell state C_{t-1} that is preserved, while the input gate incorporates the newly computed candidate values $\acute{C}_t$:

$$C_t = f_t.C_{t-1} + i_t.\acute{C}_t \quad (6)$$

This equation maintains a balance between retaining past information through the forget gate and introducing new information via the input gate.

The output gate determines the value of the hidden state h_t, which serves as the output of the LSTM cell and is passed to the next time step. The output gate is based on the updated cell state C_t, filtered by the output gate:

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (7)$$

The hidden state is then computed as:

$$h_t = o_t.\tanh(c_t) \quad (8)$$

Where: W_o is the weight matrix for the output gate, b_o is the bias term, o_t determines which parts of the updated cell state C_t will be used to compute the new hidden state h_t.

In time series forecasting, LSTM models are trained to learn dependencies in sequential data through backpropagation through time (BPTT). During training, the weights $W_{f,}$ $W_{i,}W_{C,}$and $W_{o,}$ are adjusted based on the error between the predicted output and the actual values. When processing a sequence of past data points x_1 , $x_{1,.........}$ x_t , the LSTM updates its cell and hidden states iteratively, allowing it to capture both short-term patterns (through immediate updates to the cell state) and long-term trends (by retaining relevant past information).

During the prediction phase, the hidden state h_t is used to forecast the next value in the sequence, leveraging the temporal dependencies learned during training.

LSTMs excel in retaining long-term dependencies due to their gate mechanisms. The input gate selectively stores relevant information in the memory cell, while the forget gate discards irrelevant information, ensuring that significant information is retained over time. The output gate determines which parts of the cell state are used for generating the LSTM's output. These gates adapt dynamically based on the current input and preceding hidden state, enabling LSTMs to capture long-term dependencies effectively. The LSTM architecture, with its sequence of interconnected cells, provides a powerful tool for processing and analyzing sequential data across time.

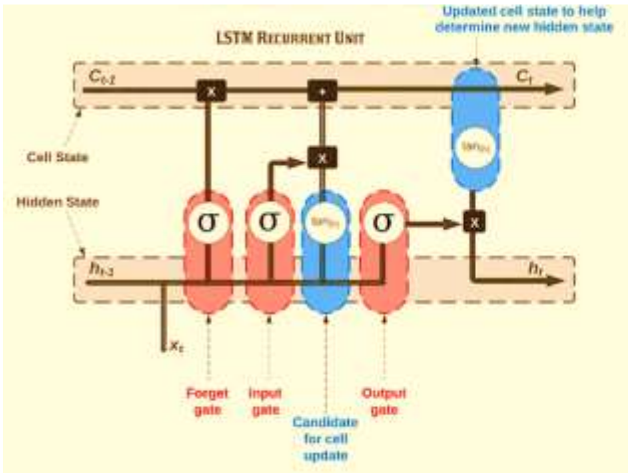
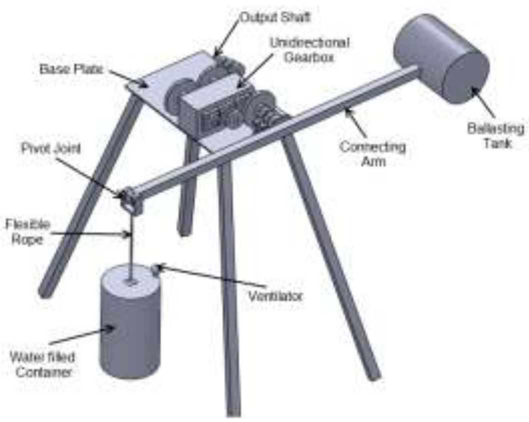


Figure 2 Structure of LSTM [13]

Experimental setup

The model's concept [14] can be grasped from Figure 2. The setup comprises a steel framed oscillating arm suspended from a non-buoyant body using a metal rope at one end and a counter weight at the other end. The arm pivots at its center, where it is linked to a rotatable shaft. The rotatable shaft is connected to a unidirectional gearbox, a step-up gearbox, and a generator. When the wave crest nears the semi-immersed container, the container's effective mass decreases due to the rising water level, causing the arm to become unbalanced. Subsequently, the counter mass lifts the container and causes the arm to oscillate in one direction. As the wave trough approaches the container, the container's effective mass increases due to the lowering water level, making the container heavier and causing it to move upwards. This alternating balancing action keeps the arm oscillating continuously. The oscillation is transmitted to the unidirectional gearbox through the rotatable shaft, which is linked at the center of the oscillating arm. The unidirectional gearbox then converts low-speed, high-torque rotation into high-speed rotation through a step-up gearbox, immediately followed by the generator for electricity generation. For performing the latching control, a brake shoe is integrated along with the flywheel of the WEC which is provisioned to operate manually and mechanically.



(a) (b)

Figure 2 (a) Solid model (b) Experimental Setup

Results and Discussion

The primary aim of this study is to predict the latching time of the non-buoyant type WEC, thereby establishing it as the output variable within the formulated model. The displacement of the WEC is attributed to the arrival of waves. Consequently, critical parameters such as wave height (measured in centimeters), time period (measured in seconds), heave motion (also measured in centimeters), power output (measured in watts), and latching time (measured in seconds) are identified as the input variables. The LSTM model utilizes approximately 5000 data points collected from a laboratory campaign, which were employed for both the training and testing phases of the developed models. Out of the collected data, 70% was allocated for training and validation purposes, while the remaining 30% was reserved for testing [15]. The TensorFlow platform was chosen for the development of the model, with metrics such as Mean Squared Error (MSE) and Mean Absolute Error (MAE) being utilized to ensure the accuracy of the developed model. The power output from the latching control, obtained through both analytical and predictive methods, is presented in Table 1. It is observed that there is a significant improvement in the output power of the predicted latch timing. The predictions generated by the model are validated through experimental setups under both regular and irregular wave conditions, as illustrated in Figures 2 and 3. The experimental results indicate that for both regular and irregular wave conditions, there is a significant improvement in the output power.

Table 1 Comparison between experimental and prediction results

Wave height (centimeter)	Time period (second)	Heave latching time (second) Analytical	Power output (W)	Heave latching time (second) Prediction	Power output (W)
10	2.1	1.1	2	1.2	2
10.7	2.24	1.2	2.1	1.2	2
11.5	2.55	1.32	2.21	1.31	2.45
11.9	2.58	1.44	2.3	2.2	2.8
12.5	2.6	1.50	2.45	2.35	2.8
13	2.64	1.55	2.54	2.6	3.2
14.5	2.78	1.62	2.7	2.8	3.5

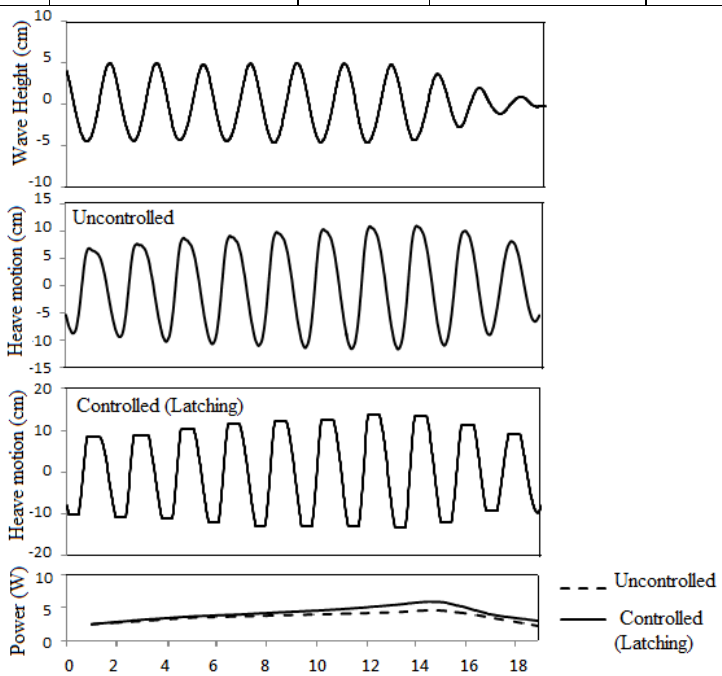


Figure 3 Heave motion for uncontrolled and latching control in regular wave

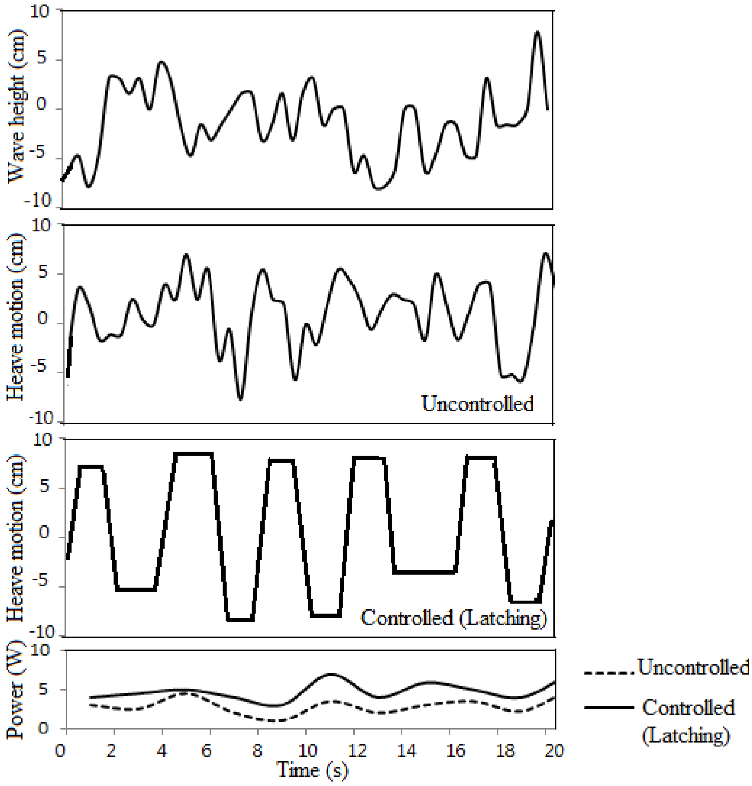


Figure 4 Heave motion for uncontrolled and latching control in irregular wave

Conclusion

This work effectively developed a LSTM model aimed at predicting the latching time of a non-buoyant WEC, utilizing critical parameters including wave height, period, heave motion, and power output. The model was trained and validated using a comprehensive dataset of 5000 data points collected from a controlled laboratory campaign, and subsequently tested on the TensorFlow platform. The findings revealed notable enhancements in power output when the predicted latching times were implemented, especially under both regular and irregular wave conditions. The accuracy of the model was verified using metrics such as MSE and MAE, which were found to be 0.09 and 0.2, respectively, highlighting the potential of artificial intelligence-driven optimization in improving the efficiency of wave energy converters. This research underscores the potential of predictive modelling in the advancement of renewable energy technologies.

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